Aalto University
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ARCHETYPES OF ARTIFICIAL INTELLIGENCE UTILIZATION

How companies create and capture value from a novel business technology

Master's Thesis
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Abstract of master's thesis

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Abstract

Artificial Intelligence (AI) has gained tremendous interest and traction in business use during few recent years. This has created a demand for more strategic understanding of its use and its capabilities in a business context. The core question, then, is how does AI create value for the companies who use it in their business and how do the companies capture that value?

In order to understand and materialize the value creation mechanisms of AI in business use, this thesis constructs archetypes of utilization for the technology. These archetypes serve as templates that include both examples of use within the single archetype and the strategic reasoning behind the utilization. They are general enough to provide a large variety of companies with valuable information on AI use but specific enough to also deliver real managerial value.

Academically this thesis is rooted in the scholarly discussions on innovation management, technology strategy and business model research. These domains of knowledge are studied carefully in order to understand what the salient dimensions are to assess the business decisions that have gone into the use of a certain technology, in this case AI, in various business use cases. Business model research is especially important in this regard as a source of literature because of its focus on the questions of value creation and capture from technologies and products with latent value.

The main research question is the titular question: What are the archetypes of AI utilization? In order to map out answers to these questions, 12 industry experts were interviewed from four different companies. These companies included both AI vendors and AI end users and the informants came from a wide variety of backgrounds, from data science to business development.

The first archetype of AI utilization that is identified by this thesis is the Cost-Saving archetype. The utilizations that are classified under this archetype aim to reduce the costs of the organization by using AI, typically machine learning, technologies and thus create value for the organization. This value then can be passed on to the customer of the organization by the way of either lowered prices or higher R&D investments which may translate into improved products. The second archetype is the Customer Engagement archetype. Here, AI is integrated into the core product of the organization to produce a better customer experience and to drive sales and/or customer retention, making it an investment towards the core product. Lastly, the Auxiliary Benefits archetype relies on AI projects generating auxiliary benefits to the organization, such as ammunition for marketing or organizational learning for the future. These archetypes are depicted using a composite model built from the literature examined by this thesis and contain a large amount of strategic information that managers and organizations can exploit at will.

Keywords Artificial intelligence, Innovation management, Technology strategy, Business models

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Tiivistelmä

Tekoäly on liiketoimintateknologiana nostanut viime vuosina voimakkaasti profiiliaan niin keskustelun kuin käytönkin osalta. Tekoälyteknologiat ovat siirtyneet hitaasti, mutta varmasti osaksi valtavirtaa. Tämä on lisännyt tarvetta tekoälyn strategisten käyttöperusteiden ja -tapojen tutkimiselle. Ydinkysymys onkin, että miten tekoälysovellutukset käytännössä luovat arvoa niitä käyttäville yrityksille ja näiden yritysten asiakkaille? Näiden arvonluontimekanismien ymmärtämiseksi ja materialisoimiseksi tämä Pro Gradu -tutkielma luo teknologian käytön arkkityyppejä tekoälylle. Nämä arkkityyppiset käyttötarkoitukset toimivat eräänlaisina malleina, jotka sisältävät niin käytön esimerkkejä kuin strategisia perusteita. Ne keskittyvät arvon luontiin ja arvon luonnin menetelmien ja mekanismien selittämiseen.

Tutkielma on osa innovaatioiden johtamisen, teknologiastrategian ja liiketoimintamallien tutkimuksen muodostamaa akateemista keskustelua. Nämä ovat aihealueita, joita tutkielma käsittelee erityisen tarkasti ymmärtääkseen ja esittääkseen sen, että millaisia liiketoiminnan ratkaisuja teknologian käytön, taustalla tyypillisesti ja toisaalta tässä tapauksessa on. Liiketoimintamallien tutkimus on tässä mielessä erityisen tärkeää, sillä tämä liiketoiminnan tutkimuksen haara nimenomaan keskittyy arvon luonnin ja tuotannon taustalla oleviin kysymyksiin ja siihen, että miten teknologioiden sisällä oleva, latentti arvo saadaan esiin.

Pääasiallinen tutkimuskysymys käsittelee sitä, että mitkä ovat tekoälyn käytön arkkityyppejä. Tämän ymmärtämiseksi tutkielmassa haastatellaan 12 tekoälyteknologioiden asiantuntijaa, jotka edustivat neljää eri yritystä. Nämä yritykset olivat sekä tekoälyn tuottajia että loppukäyttäjiä.

Tutkielma tunnistaa kolme tekoälyn arkkityyppistä käyttötapaa. Näistä ensimmäinen käsittelee tekoälyä kustannussäästöjen tuomana. Tässä arkkityypissä tekoälyn sovellutusten, tyypillisesti koneoppimisjärjestelmien, tehtävä organisaatiossa on tuottaa tehokkuutta ja kustannussäästöjä automaation kautta. Arkkityyppi luo loppuasiakkaalle arvonlisäystä mahdollisesti matalampien hintojen tai parempien tuotteiden kautta, mutta yrityksellä on lopulta valta päättää arvonlisäyksen kohde. Toinen arkkityyppi, asiakkaan sitouttamisen arkkityyppi, taas näkee tekoälyteknologiat investointeina organisaation ydintuotteeseen. Arkkityypissä tekoälyllä parannellaan ydintuotetta, jonka toivotaan johtavan parempaan asiakaskokemukseen ja sitä kautta suurempaan asiakaslojaliteettiin. Kolmas arkkityyppi taas luo arvoa tekoälysovellutusten sivuvaikutusten kautta. Tällaisia sivuvaikutuksia ovat esimerkiksi tekoälyprojektien hyödyt markkinoinnissa ja organisaation projektien myötä kasvanut sisäinen tietotaito tulevaisuutta ajatellen. Nämä arkkityypit esitetään käyttäen tutkielmassa kirjallisuuden pohjalta luotua komposiittimallia ja ne sisältävät merkittävän määrän strategista tietoa johtajilla ja organisaatioille hyödynnettäväksi.

Avainsanat Tekoäly, Innovaatioiden johtaminen, Teknologiastrategia, Liiketoimintamallit

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Helsinki, August 17 2018

Selim Saukkomaa

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1 Introduction

In his book on the quest for reaching a general artificial intelligence (AI) capable of any kind of tasks that the user throws it, University of Washington's professor of computer science Pedro Domingos writes (Domingos, 2015):

> "We train a neural network to recognize horses, but it learns instead to recognize brown patches, because all the horses in its training set happened to be brown. You just bought a watch, so Amazon recommends similar items: other watches, which are now the last thing you want to buy. If you examine all the decisions that computers make today–who gets credit, for example–you'll find that they're often needlessly bad. [...] People worry that computers will get too smart and take over the world, but the real problem is that they're too stupid and they've already taken over the world."

While humorous, Domingos' point is real. Different sets of algorithms that we might for simplicity's sake collectively call "AI" already make countless decisions in our daily lives but they are far less sophisticated than our imaginations seem to think. Technologies that might be classified as AI do not power killer robots but are used for cooling server halls, optimizing delivery routes and other routine, everyday tasks that are virtually invisible. On the other hand, AI is seen as an existential threat to humanity and a near-infinite source of power. For example, the president of Russia Vladimir Putin has recently stated that "Whoever becomes leader in this [AI] sphere will become the ruler of the world." (Vincent, 2017). Elon Musk, the CEO of the electric vehicle company Tesla, meanwhile seems to believe that the ramifications of AI competition are so severe that it is in fact the most likely cause of the third world war (Musk, 2017). It seems that views on the topic have a range and a hyperbole that is almost uncomparable to any technology development seen in decades, save for perhaps the internet. This creates an interesting opportunity to attempt to understand the real business uses of such a technology by analyzing its mechanisms of value creation and capture, and to tie them into a larger, historic academic context.

Rodney Brooks (2017), the former director of the Computer Science and Artificial Intelligence Laboratory at MIT reminds us of a concept called Amara's Law when talking about AI, named after the Silicon Valley pioneer Roy Amara. Amara's Law states that in the short term the effect of a technology tends to be overestimated and in the long term the effect tends to be underestimated. Brooks goes on to note that GPS technology, for instance, almost perfectly followed Amara's Law: when the initial batch of GPS satellites were launched to the orbit in 1978, the technology saw little use or success. It was only over 10 years later during Operation Desert Storm that the potential of GPS was unearthed not only to the U.S. Military but the public at large. Now then, GPS could be said of being in the “long run” part of Amara’s Law: It’s used in a myriad of applications from industrial farming to video games. Brooks stresses that AI has been overestimated time and time again, especially historically speaking and that more attention should be given to the question of how long exactly is the long term of AI.

1.1 Research objectives

The reasoning for producing a thesis on this topic right now is simple yet equally important. As the surge and interest of cloud computing has risen due to rapid decreases in hardware costs and the advent of complex, powerful multi-core computer architectures (Foster et al., 2008) and, at the same time, the amount of data that consumers have created for platform-holders has multiplied exponentially thanks to a wealth of sensors, apps with thousands of interactions and touchpoints into ordinary life of consumption, resulting into 16.1 *zettabytes* (a zettabyte is a trillion gigabytes) of data generated in 2016, which is estimated to grow tenfold by 2025 (Reinsel, Gantz and Rydning, 2017). Due to this combination of events, the notion of powerful AI has gone into mainstream and become a reality.

As to illustrate this one could examine the amount of investments that go into AI on an annual basis. Total investments (both external and internal) by companies into AI reached a figure between $26 billion to $39 billion in 2016 (Bughin, et al. 2017). Despite of this, there seems to exist plenty of confusion as to what are the actual prospects of AI in business use. What are the typical ways of utilizing AI? Can we learn something about AI from the literature on exploiting technologies in business about the vector of applications of AI in business? How does AI create value for those who choose to utilize it? These are the examples of the type of questions that this thesis is an attempt to answer.

Another motivation that might be prudent to mention is the desire of understanding and discerning reality from the hype. As an example of the relative “hotness” of the topic, within a timespan of a year it most major management consulting companies have released a research paper or a report concerning AI and its capabilities of transforming business (Accenture, 2016; McKinsey, 2017; Boston Consulting Group, 2017; Deloitte, 2016; PwC, 2017). In addition to this, the Ministry of Economic Affairs and Employment of Finland recently released its own strategy document (Työ- ja Elinkeinoministeriö, 2017) detailing the actions of the Finnish government in order to exploit AI technology in the near future.

The existence of these publications does seem to point towards a thirst for information about the nuts-and-bolts practicalities of AI and AI utilization. This is an area of interest for myself as well: understanding the real prospects of AI from the abundant hype surrounding it. This relatively hype-free approach to AI seems to be quite topical. On the 6th of November 2017, three consultants in charge of AI projects at a Finnish technology consultancy Reaktor wrote a joint op-ed piece to the Finnish business daily *Kauppalehti*, arguing for more realistic, holistic discussion of AI applications for businesses. In the op-ed, they note that while, for example, internet package transfer protocols were the building blocks of the first versions of the internet itself, not many people are focusing on the technology of package protocols in 2017, while they are still using them on an everyday basis. AI may progress into a similar direction, where it becomes so invisible and integrated into everyday applications that it will be seen more of a utility than anything else. The authors of the op-ed also go on to note that in order to reach its full potential AI requires work, experimentation and long-term investments and that there indeed is no generic solution for AI (Himberg et al., 2017). This thesis is largely the study of these exact concepts and ideas. By exploring and unearthing different ideologies of utilization that have started to form around the nascent commercially viable AI technologies, this thesis aims to understand the business thinking behind those utilization strategies by examining their strategies of value creation and capture. Thus, it contributes to the academic discussion of innovation management, technology strategy and business model research through the topic of AI utilization in business.

1.2 Research questions

This study aims to find out in concise and clear terms, what different archetypes exist and are in the development pipeline for utilization of AI in a business context. The study will provide scholars and managers alike a set of archetypes that can be used for identifying and classifying different utilizations of AI in business. By an archetype, this thesis refers to the idea of an archetypical utilization model that covers multiple different singular utilizations of a given technology but not all of them. An archetype contains an ideology that is behind its understanding of what value is, how it is created and captured and why certain decisions are taken. These archetypes and their strategic reasoning are materialized through business decisions which are interpreted through concepts from business model research. In other words, the thesis uses a business model research framework to understand the motivations, goals and strategic thinking behind the archetypes, in addition to their outright content and form. The primary research question is as follows:

- What kind of archetypes of AI utilization can be typologized based on the business decisions that companies have taken in relation to AI?

This divides into three subquestions as such:

- What kind of business challenges do AI utilizations address?
- What are the critical competences required for successful AI utilization projects?
- What are the business model implications of AI projects?

For the study, two groups of companies are examined: AI vendors, companies who design and produce commercial AI solutions, and AI end users, companies who implement these solutions to their businesses. The study approaches this subject via the rich and active literature stream of technology exploitation, strategic technology use in organizations and business model research to understand what different styles of utilizing AI have emerged so far. By reading this study, the reader should be able to recognize different archetypical AI uses in organizations and start utilizing this information in their own organization as well.

1.3 Structure of the thesis

The study approaches the topic of practical AI utilization in companies through a collection of streams of business research literature from recent decades. The literature will mostly be drawn from the domains of innovation management, technology strategy and business model research. Of these streams, most are fairly self-explanatory with perhaps the exception of the business model research literature stream. However, this is an extremely important research domain from the perspective of understanding the decisions that have gone into the different instances of AI utilization and application so that archetypes can be built from those utilizations. Business model research deals a great amount in ambiguous strategic situations that pertain to novel technology use and technological shifts that may require shifts in the organizational behavior of the company (Govindarajan and Trimble, 2005). The literature stream is extremely interested in the nature of value and how it is created in changing business circumstances (Christensen, 1997; Desyllas and Sako, 2013). Being that circumstances around AI are changing at such a rapid pace and the question of value creation looms over it so heavily, this stream of research provides the thesis with ample tools to analyze and examine the decisions and to effectively decode the strategic and operational reasoning behind AI utilization projects and allowing the thesis to reach the abstraction level that is needed in order to build archetypical utilization models for AI. A composite model of an archetype of utilization is built at the end of chapter 2 from key scholarly concepts of the streams of literature that are used as a basis for this thesis. This model will be used in depicting the utilization archetypes that emerge from the empirical data in chapter 4.

From a methodological perspective, the idea of developing archetypes of different models of approaching a topic in a business is not the most common one but it does have precedents that can be used as a guiding path. An excellent example of this approach to business research can be found in Bocken et al. (2014). In the study, the authors posit that the aim of this type of an avenue is to develop a common language that can be used to accelerate the development of the field that is under study, in their case sustainable business models and in my case AI utilizations in business. They also note that the idea of creating archetypes is to describe groupings of mechanisms and solutions that may contribute to the goal at hand. As an outcome, I am highly interested in achieving something similar with my thesis as well: a cohesive and descriptive language that clarifies something that is quite abstract and suffers from a high amount of unspecificity.

This study uses case research as a research method. Case study as a research method usually arises from a desire to understand complex social phenomena and it allows the researchers to retain the holistic and meaningful characteristics of real-life events, such as organizational and managerial processes for instance (Yin, 2009). This is why it make sense going forward with a case study methodology where essentially two groups of informants classified by company type that are involved in creating, selling and purchasing utilizations of AI will serve as two distinct cases that can be compared when needed. Accordingly, the empirical data used for this thesis consists of interviews of two sets of industry professionals: AI creators/vendors (design and technology consultants) and AI utilizers (banks, private healthcare companies, startups). Based on this interview data, the archetypes for AI utilization will be built, as previously discussed. In addition, the research subquestions will be answered as well, as they focus on questions that are not necessarily directly related to the archetypes of AI utilization but are important within their own right in order to understand what kind of solutions and resources AI utilizations require from an organization and what are the strategic implication of those archetypical utilizations.

The method is similar to what Yin (2009) describes as a multiple-case study. Yin goes on to say that in the past there has been a mistaken analogy of mixing up multiple-case studies with the idea of creating a survey and having multiple respondents to answer that survey. A much better idea would be to treat the cases in a multiple-case study as replications of an experiment: if significant findings are found from a single experiment, usually a pressing priority would be to attempt to replicate these findings by conducting additional experiments. Yin adds that a rich theoretical framework is needed for an approach like this: the framework needs to state the conditions under which a particular phenomenon is likely to be found as well as the conditions when it is not likely to be found, making the theory serve as a practical tool for understanding reality. With the interview data, I will return to the literature and create a dialogue between the empiria and the literature, to see if a new kind of typology of utilizations for AI could emerge.

Speaking of connecting theory and reality, Dubois and Gadde (2002) discuss this type of an approach to the interplay of theoretical domains of knowledge further, dubbing it "systematic combining". They break down the idea of systematic combining into two distinct processes: the process of matching theory and reality and the process of direction and redirection. These processes are then influenced by four factors: what is going on in the reality, available theories, the case that gradually evolves and analytical frameworks. The authors go on to state that most textbooks on research methodology fail to make use of the opportunities that are embedded in the intertwined nature of the case study. They often seem to describe case studies as linear approaches, as stories that unfold with a beginning, a middle and an end. Instead of treating cases as linear paths of the truth, the authors recommend an approach where the researcher goes constantly back and forth from one type of research activity to another and between empirical observations and theory, making it possible to expand the understanding of both of these. As mentioned before, based on the extant research literature, a model of a utilization archetype will be built and the interview data will be analyzed in relation to this model. However, this model is not immutable, in fact far from it: if the interview data makes parts of the model irrelevant and/or obsolete, the model shall be then modified on the basis of further literature that will be examined. This is to say that while building a model that the interview data will be "fit" may seem deductive, it is actually more inductive in its nature: the model only serves as a preliminary set of assumptions and a tool that the data can be analyzed with. If the data clearly overflows the boundaries of the model, a more suitable model shall be devised. This is something that is very much connected to the approach of systematic combining where Dubois and Gadde (2002) refer to this preliminary analytical framework as "articulated preconceptions". These preconceptions then are developed over time according to what is discovered through empirical fieldwork and through analysis and interpretation since theory cannot be understood without empirical observation and vice versa. To summarize, the authors describe systematic combining as "[...] a nonlinear, path-dependent process of combining efforts with the ultimate objective of matching theory and reality.". This thesis aims for a similar approach as it suits the nature of the topic with its inherent tensions between feasibility and optimism quite well.

2 Literature review

While scholarly discussion of AI has existed for decades, it has mostly resided on a conceptual and technical level rather than a strategic or a business level. AI, for most of its life, has lived a quiet life as a niche sub-branch of computer science and mathematics with little to no practical applications. Russell and Norvig (2009) suggest that roots of AI can even be traced as far back as 384 B.C. with the birth of Greek philosopher and scientist Aristotle and the subsequent birth of modern western philosophical thought. Aristotle was one of the first western philosophers to come up with a precise set of laws governing the rational part of the mind and developed a system which allowed one to generate conclusions mechanically given initial premises. While this is certainly one way of analyzing the genesis of the scientific field of AI, most people would time the birth of "modern" AI thought to the 1950s in the United States of America, with such pioneers working simultaneously as Marvin Minsky, John McCarthy, Claude Shannon, Allen Newell and Herbert Simon. Most of these researchers convened in a landmark summer conference in Dartmouth College in New Hampshire, United States during the summer of 1956 to lay foundations to the field as a formalized area of research (McCorduck, 1977).

This literature review essentially contains two parts which are thematically separate but conceptually linked by this thesis. In the first part, in chapters 2.1, 2.2 and 2.3, AI as a concept is discussed, defined and its relationship with disruptive technologies is examined more closely. These chapters ensure the construct validity of the research and should serve as a practical guide to the reader as to how the author sees AI and its relationship with the outside world, particularly that of business. In chapters 2.4 through 2.9 the literature review shifts gears and focuses on innovation management, technology strategy and business model research literature. These knowledge domains serve as the core source material for the framework for depicting archetypical AI utilizations which is presented and discussed in chapter 2.9.

2.1 On the definition of "AI"

Before discussing AI, it might be prudent to examine what is meant by "technology" in the context of this thesis. As technology is referenced constantly throughout the thesis as a central driver and a market-shaping force, we can already conclude that by "technology" the thesis is not referring to the material manifestations of a technology or groups of technologies. Technology then is not understood as devices, code, intellectual property or any other kind of material representation that springs to mind when casually discussing the idea of "technology". The definition of technology that is used in this thesis is the one proposed by Christensen (1997, xiii) who understands technology as "[…] the processes by which an organization transforms labor, capital, materials, and information into products and services of greater value. All firms have technologies. […] This concept of technology therefore extends beyond engineering and manufacturing to encompass a range of marketing, investment, and managerial processes." This definition of course does not exclude things like devices and code, as they may or may not fall into the criteria that Christensen lays out. The definition is inclusive in its nature in order to better understand and examine the myriad outcomes of AI as a technology itself. Astute readers may draw a rather direct link to Bigelow's (1831, vii) classic definition of technology as a word and concept as "[…] the principles, processes and nomenclatures of the more conspicuous arts, particularly those which involve the applications of science, and which may be considered useful, by promoting the benefit of society, together with the emolument of those who pursue them." Despite its age, it reads as what is essentially a different wording of Christensen's definition that was portrayed above: it even packs in the economic logic of technology transforming inputs into something that is of higher value by explicitly referring to the emolument of the pursuer of a technology. Both of these definitions are of course quite similar to the one used generally in economics, in which technological progress essentially refers to the human efforts of increasing productivity under an increasingly diverse set of environmental conditions (Rosenberg, 1982). Nevertheless, as this is a master's thesis that deals in the knowledge domain of business, however loosely defined it may be, we shall stick with Christensen's definition with appropriate credits to its intellectual foundations in Bigelow's thinking and in economics in general.

In general, different definitions of AI do exist and are often used somewhat interchangeably which poses a risk for confusion in discussion. These definitions can be grouped up into four rough categories: systems that think like humans, systems that act like humans, system that think rationally and systems that act rationally (Russell and Norvig, 2009). For now, we shall select the last category of these definitions and use the excellent definitions by Poole et al. (1998, cited by Russell and Norvig, 2009 p. 2): "Computational Intelligence is the study of the design of intelligent agents." and Nilsson (1998, cited by Russell and Norvig, 2009 p. 2): "AI[...] is concerned with intelligent behavior in artifacts.". Russell and Norvig dub this school of thinking the "rational-agent approach" and note that it has two advantages over the other types of AI typologies: First, it does not rely solely on correct inference. An AI that has been programmed to act rationally may also act when there is no optimal or, indeed, "correct" way of operating. Second, it is more suitable for scientific development than a definition based on the idea of humanity. Rationality is a well-defined concept that is relatively easy to model, unlike humanity. For the purposes of this thesis, I believe the definitions I have laid out above serve us well. Business as a logic relies heavily on the idea of rationality and choosing the optimal possibility in a given situation. These situations are not necessarily often very clear-cut and may rely on choosing the best option from an array of subpar options.

Other definitions of AI do exist and it seems that the risk of confusion is so high that AI has to be defined in every instance of discussion. To give a few examples from a completely other type of discourse, the management consulting company McKinsey (McKinsey, 2017 p. 14), for instance, states that their definition is "[...] based on an ability to learn from experience, aided by big data architecture and a new generation of self-learning algorithms.". Meanwhile, the accounting and management consulting company PwC (PwC, 2017 p. 2) defines AI as "[...] a collective term for computer systems that can sense their environment, think, learn, and take action in response to what they're sensing and their objectives.". They continue by breaking AI down into four categories of automated intelligence, assisted intelligence, augmented intelligence and autonomous intelligence.

The portrayal of these different definitions of what one might think is a fairly straightforward technical concept highlights the fact that AI is in fact a complicated system of ideas and applications which can be interpreted very differently depending on the context and the goals of the discourse itself. This is why, especially in an academic business context, it is worthwhile to make sure that the author and the audience share a definition of AI or at least know what definitions the other parties of the conversation are using at any given time.

2.2 Is AI a disruptive technology in the first place?

Some thought should also be given to the question of whether AI should be thought of as a disruptive technology in the first place. It is tempting to label any novel technology as disruptive, as disruption as a word is sufficiently dramatic to drive home the idea of major technological progress and/or a shift in business thinking. As with any such temptation, some rational thought should be exercised before labels are given. Christensen (1997) talks of *disruptive* and *sustaining* technologies. Most new technologies are sustaining technologies. Sustaining technologies can be radical or discontinuous in their character, but they don't necessarily have to be: the common denominator of sustaining technologies is that they improve the performance of established products, along the dimensions of performance that the product has already possessed in relation to its current customers.

The relationship between customer expectations and sustaining innovations is especially notable. Sustaining innovations sustain the rate of historical performance improvement that the customers have come to expect. Perhaps needless to say, an overwhelming majority of technological advances in a given industry are sustaining in their nature. Disruptive innovations, however, often offer worse product performance (in the near-term) and have a markedly different value proposition altogether than sustaining innovations. While they underperform in mainstream markets, they most likely have other features that customers value that are not perhaps even tracked as key performance indicators (KPIs) in the product category, as they are so novel in their nature. They are often cheaper, simpler and start at a lower part of the performance chart compared to their established counterparts and typically surpass them at a later stage. Disruptive innovations, according to Christensen, usually appear when the current product hegemony starts to deliver *performance oversupply,* meaning that the available technologies start providing performance improvements that are above the required level of the market.

Radical innovations should not either be outright confused with disruptive innovations. While disruptive innovations can be radical innovations, radical innovations are not necessarily disruptive innovations. Christensen (1997) offers an example of this, referring to the excavation industry in the United States during the 1920s. The industry faced a significant technological change in shifting from steam-powered excavators to gasoline-powered excavators, which were built using an entirely different product architecture. However, the marketing position of the industry did not change and neither did the clients. The value proposition remained exactly the same: moving large masses of land efficiently. Thus, gasoline excavators were a radical technological shift from steam excavators, but they did not disrupt anything. Later on, the excavator industry faced another technological shift from cable-actuated shovels to hydraulic shovels, which featured significantly smaller bucket sizes, i.e. worse performance in the central performance metric of the industry. Hydraulic excavators found their clientele in newer, unexplored markets that demanded more mobility and precision as opposed to power and size and proceeded to overtake the mechanical excavator market altogether. This represented a disruptive force in the excavator industry. While all the major excavator companies survived the shift from steam to gasoline, almost none survived the shift from cables to hydraulics, even though the size of the technological shift was more or less similar. This was simply due to the fact that hydraulic excavators didn't make sense, until they suddenly did and by then it was already too late to act. This may explain some of the bullishness exhibited by firms towards AI as well. Whether AI is a disruptive innovation or not may be ultimately a meaningless debate from the perspective of the firms since the cost of not investing at an early stage may indeed be grave. As it is still relatively early in the development cycle of commercially viable AI products, it is not easy to assess whether AI is sustaining the innovation that has already happened or it is disrupting it.

As later discussed in chapter 4, AI is certainly making its way into products, services and processes of companies, but is it truly changing the value proposition of those products? Henderson and Clark (1990) speak of architectural innovations which are often triggered by a change of a component which in turn creates new interactions with the other components in a given product architecture. However, the essential design concept behind each component stays more or less the same. While indeed Christensen (1997) seems to believe that achieving and managing disruptive innovations is nigh-impossible for established firms, Henderson and Clark (1990) present architectural innovation as a subtler form of a similar challenge, noting that architectural knowledge in the firm can be tricky to manage because it is so embedded into the day-to-day operations of the firm. Perhaps this is what AI is for many established companies as well, an architectural innovation, residing somewhere in between the axis of incremental and radical, of sustaining and disruptive.

According to Christensen (1997), disruptive innovations almost always feature simpler product architectures than previous approaches and less of what customers in established markets desired, making them essentially unimportant to the mainstream until their breakthrough, which typically occurred much later. This is perhaps where the age of Christensen's argument begins to show. The question of what a simpler product architecture is in the first place is a considerably more complicated one in 2018 compared to 1997, when a simpler product architecture was nearly synonymous with worse features, lower-quality components and an overall inferior experience. As product-service combinations are now much more complex and on the other hand much more software-based than 20 years ago, simplicity may have inherent value it didn't necessarily have in 1997. Danneels (2004) reaches similar conclusions in his critique of Christensen's seminal work, noting among other things the vague nature of the label of "disruptive". Is disruption a simply a matter of perspective? Are different technologies disruptive to different companies even within the same industry? Danneels offers his own definition of a disruptive technology, stating that "A disruptive technology is a technology that changes the bases of competition by changing the performance metrics along which firms compete." (Danneels, 2004: p. 249). This is an intriguingly elegant version of Christensen's basic idea which is probably more suited for an era with more complicated, systemic products and services. This definition also suits well for the analysis of AI, a technology which essentially trades human understanding of abstract, interlinked subjects for speed, prediction capabilities and scale. It is most likely too early to tell whether AI should be labelled a disruptive technology or not, but it is important to contextualize it as something that may be disruptive, at least to someone, somewhere.

2.3 Discourses on AI

As established earlier, AI, when not defined more specifically and spoken more of as a concept, is somewhat ephemeral and general. In this way it truly can be seen more as a flexible platform or a utility that enables other outputs and business outcomes. It should be said that AI can be spoken of in a concept-like manner, where it is simply generalized as a group of technologies that receive certain inputs and produce certain outputs based on those inputs from material that is not familiar to them, or it can be spoken of in a more technical, exact manner where the discussion turns into specific algorithms and other mathematical minutiae. This holds true for utilities as well: Electricity is fairly self-explanatory, but if needed to be it can be discussed in exhaustive technical detail. This is to say that while talking about AI as a utility-like group of technologies may seem reductive, it is merely an effective tool for discussing the business value and outcomes of a very complex system of mathematical concepts.

Still, even utilities like package protocols or plumbing have different use cases, pros and cons and value propositions. In this section, I will introduce different typologies of artificial intelligence as presented by various stakeholders who have thus far taken part in the conversation in order to get an understanding of existing ways of categorizing and understanding AI technology. These takes roughly divide themselves into three distinct discourses: a business discourse that is largely led by white papers from management consultancies, technology consultancies and other professional services firms that seek to promote the field itself and their own expertise in it, a technical discourse that takes place in scientific journals and blogs that focuses on the technical aspects of AI and the practical mathematics of it which seeks to drive forth technical development and understanding of AI and lastly, the public discourse which at least until now seems to have focused more on the societal issues of AI, such as employment, automation and disruption. These "streams" of discourse are of course fluid in their nature and actors do take part in multiple discourses on a fairly regular basis, but for the purposes of this thesis this is a typology that serves our purposes well. They also reflect the multidimensionality of this particular topic, where constructs, sentiments and conventions vary wildly depending on the discourse that is being partaken in.

2.3.1 The business discourse of AI

The business discourse of AI is extremely active in the form of consultancy white papers, strategy reports, market research and other material that falls to the grey area between marketing and what might academically be called research. Their primary function is, of course, to showcase the analytical thinking and the proficiency of the consultancy in hopes of gaining new clients. However, they also showcase the strategy and, perhaps even more importantly, the attitude that the particular consultancy has towards a technology and how bullish they feel about the prospects of it. Typically, the discourse presents AI as a problem that is solvable if the right tools are found. This is of course due to the business model of a management consultancy. A problem needs to be framed as difficult and complex enough that it requires the services of a consultancy to solve it but feasible enough to solve that once those services are acquired the customer will receive a return on their investment promptly.

Chui, Manyika and Miremadi (2018) is an example of this type of discourse. In their report for the global management consultancy McKinsey (all three authors are McKinsey employees) they formulate AI as a promising, yet challenging technology which may bring value to the organization but only if certain conditions are met. A direct quote reads "If you want to become a leader who understands some of the critical technical challenges slowing AI's advance and is prepared to exploit promising developments that could overcome those limitations and potentially bend the trajectory of AI—read on." (Chui, Manyika and Miremadi, 2018, p. 3). Purdy and Dougherty (2017, p. 3) in their report for Accenture, another management consultancy, paint a similar picture of AI as a profit boosting technology with certain caveats that (presumably) the company will help their clients with: "Accenture research shows that AI has the potential to boost rates of profitability by an average of 38 percent by 2035 and lead to an economic boost of US$14 trillion across 16 industries in 12 economies by 2035. But this will only happen if organizations adopt a people-first mindset and take bold and responsible steps to apply AI technologies to their business. Our research has identified eight cross-industry strategies to help seize the AI opportunity." A similar, ominous tone can be found in the closing words of Ransbotham et al. (2017, p. 15) which is a joint effort by *MIT Technology Review* and the management consultancy company Boston Consulting Group: "Just about any company today needs a plan with respect to AI. Most do not have one, and those that have been slower to move have some catching up to do. Those that continue to fall behind may find the playing field tilted evermore steeply against them.". This is the tone of the discourse in several other examples as well (Deloitte, 2016; Accenture, 2016; PwC, 2017). AI is presented as a challenge that needs to be solved because the stakes are hand are big. A winner will emerge who will take home the pot.

One might argue that this thesis is a part of this same continuum, the business discourse on AI where AI can be "conquered" by employing certain steps and the conquerer will be rewarded duly. It is true that this, after all, is a master's thesis in business and as such it has a managerial tone which assumes that with a certain sequence of steps it is possible to profit from a technology more readily than the competitors. In this sense the idea that this thesis itself is a part of the business discourse on AI is certainly possible even though the motivations for it are not commercial.

2.3.2 The technical discourse of AI

The technical discourse of AI looks strikingly different from the other two discourses defined here. Here, the confidence about the capabilities of AI seems to be significantly lower than in other discourses and the definition of terminology and technical realities is of paramount importance. Both of these facts are of course understandable, as the technical discourse and the actors who engage in it are exposed to the reality of AI technologies on a daily basis through their work and as can analyze the prospects of the technologies far more accurately. At the same time, this certainly can create a rather myopic worldview as well: When observed from great proximity, it is easy to miss the development of the large-scale picture and have a sufficiently wide temporal perspective, when assessing the recent developments of a technology. Furthermore, as already stated, the repeated failures of experiments seen from a figurative front-row seat can affect the perceived development of the field. The failures, after all, aren't widely reported on the covers of technology and business magazines and as such, don't spread into other discourses the way that the successes do.

By and large, the term "artificial intelligence" is absent from papers by scientists working on machine learning, neural networks and other technologies that one would commonly classify under the banner of AI (For examples, see Yosinski et al. (2014), Hinton et al. (2015) and Li et al. (2016). A quote by Collobert et al. (2011, p. 2494) illustrates the caution to label one's own research as research on "artificial intelligence" or, for that matter, to claim that artificial intelligence even exists: "Although such performance improvements can be very useful in practice, they teach us little about the means to progress toward the broader goals of natural language understanding and the elusive goals of Artificial Intelligence.". This is certainly understandable. While, for example, marketing would at least in the traditional business school typologizing scheme fall under the general banner of "business", marketing scholars do not make strenuous connections to such abstract, wide concepts as "business" in their papers to prove that they belong to the category. In a similar manner, AI researchers do not start their papers by defining what is and what isn't artificial intelligence, or even discuss the idea of artificial intelligence in the first place. They present a problem, their proposed solution, the results of that solution and discussion.

2.3.3 The public discourse of AI

The public discourse is, in the context of this thesis, formed by the media and public institutions. While these have severely different operating mechanisms, motivations and goals, they do share an important trait that needs to be considered, especially in light of the sentiment on AI: They both shape public opinion in a manner that the technical discourse nor the business discourse can. The other two categories of discourse are aimed at professionals who either work with AI right now or may work with AI in the near future. The public discourse is for the rest of us. This matters to a tremendous degree because the public discourse shapes the public sentiment of AI which in turn shapes investments to AI, at least to a degree.

The tone of the conversation on AI in the media and from public institutions has been diverse, but some general lines of conversation can be found. It seems that while there is plenty of AI alarmism and fear, it shares a stage with an interest in the topic and a curiosity of what might be next in the field. While some of the earlier reporting on AI may have been quite frightened in its approach this has now reached a plateau of compromise where a certain degree of responsibility is being expected from companies that develop AI and in turn from the consumers as well. *The Guardian* (2018), for instance, writes: "Questions about the ethics of artificial intelligence are questions about the ethics of the people who make it and the purposes they put it to. It is not the monster, but the good Dr Frankenstein we need to worry about most." *The New York Times* (2018) also exhibits this exact tone of vary, nervous curiosity: "Artificial intelligence is here — and it's bringing new possibilities, while also raising questions. Do these gadgets and services really behave as advertised? How will they evolve in the years ahead? How quickly will they overhaul the way we live and change the way we do business?". A very similar tone can be seen in Lohr (2016), a story in *The New York Times* about an alternative way of developing AI, titled ". Is There a Smarter Path to Artificial Intelligence? Some Experts Hope So". The very title itself sets the tone: AI is here, it's going to stay but we don't need to make it terrible. Another article in *The Guardian* newspaper says in its headline "Killer robots will only exist if we are stupid enough to let them" (Devlin, 2018), implying the responsibility of the companies and the consumers.

While the public discourse is not as positive on AI and its effects as the business discourse, one would not characterize it as unanimously negative either. It seems to be reaching a point of a certain amount of maturity where the realities of artificial intelligence and its development are now being confronted.

2.4 Diffusion and exploitation of technology

A potential avenue for approaching the topic of archetypes of AI utilization in organizations is to by starting the construction process of a knowledge base from the rich academic literature concerning diffusion, exploitation and adaptation of technology and innovations. While certain new technologies were rather self-explanatory in their use and utilization, say telephones or E-mail, AI is more of a concept, a mode of thinking and organizing knowledge work that requires the organization to craft a tailor-made solution. Interestingly enough Fichman (1992) notes that, indeed, some technologies can not quite be adapted as solutions ready to be bolted on on top of the organization and its business but rather that they impose a sizeable knowledge burden on the would-be adopters. He continues to remind that classical diffusion literature focuses on the would-be adopter's willingness to adopt while in all actuality in certain circumstances where knowledge barriers are high the more telling issue could be adopter's ability to adopt.

While ample literature exists and is easily available on the question of *how* technological innovations are adopted and diffused into business organizations, this thesis is more interested in the question of *what and why* are the archetypical outcomes of those adaptations, in this case AI. This is to say that while understanding diffusion mechanisms is important it is not the focus of the study.

In one of the earlier studies on the diffusion of technology and industrial applications of novel innovations, Utterback (1974) has a number of interesting things to say about the topic that are still relevant enough to discuss here. Firstly, when it comes to the origins of innovation activity and new technologies, it seems to be often stimulated by the rising costs of inputs: innovations often are initially centered around reducing the use of more expensive inputs. Utterback extends on this, continuing to say that diffusion of innovations in firms is many times a question of the extent of relative advantage the innovation offers. Relative advantage, according to the author, essentially means that either the costs associated with the business go down, the demand associated rises or the price point of the product can be hiked up due to improvement in quality. If one of these conditions apply, the firm is looking at relative advantage. Orlikowski (2000) also adds to this conversation by noting that humans interact with novel technologies in a recurrent fashion, meaning that while they constitute their understandings of a novel technology through its use, the use itself is shaped by their past actions with past technologies, which further cements and regularizes certain actions. This would certainly explain Utterback's (1974) notion that cost-saving is the first task of many new business technologies, as this has been the case previously as well and is such replicated in a continuous loop.

In addition, we should note Utterback's (1974) finding that diffusion rates of technology depend on the informal and personal communication within the company as well: As the information associated with technology is often complex, buyers have varying needs and they tend to change continuously, a flexible system of communication is required within the company, especially among the technical staff. This seems to echo the results of a later, classic study by Edmondson (1999) where the author found a direct connection between team psychological safety, the idea that team members can freely and express their thoughts and ideas without the risk of losing face, public embarrassment or loss of status within the team regardless of the outcome, and team learning capability, which in turn contributed towards team performance. As this team learning capability seems to be also what Utterback (1974) is implying, we can relatively safely assume that AI technology, as any new organizational technology, requires a certain amount of psychological safety within the organization and across teams and technical personnel in that organization to facilitate an environment where it can thrive.

Chesbrough and Rosenbloom (2002) note that in order to access the latent value in technology, a business model of some sort must be applied to it in order to extract the value. This business model may be the same business model that the company uses currently but it may also require the managers of the company to expand their perspectives and find a suitable solution from outside of the current limits of operation. This is critical as a point to examine when searching for different archetypes of AI utilization in companies as it may be possible to identify whether the company has adopted a utilization archetype that has required it to make changes in its business model (or indeed, its entire *raison d'être*) or it has managed to fit AI into its current business model(s).

The act of fitting novel technologies into an existing business model or a strategy has interested scholars in the recent decades. Servitization, according to Vandermerwe and Rada (1988), is the act of bundling offerings into customer-centric combinations of goods, services, knowledge and self-service in order to achieve higher amount of value delivered to the customer. This line of thinking is quite salient in relation to AI since, as discussed previously in this chapter, AI is a technology that requires a significant amount of refining and understanding in order to deliver value to the end user. This, of course, is a natural path for a new technology to take especially when looking at the recent history of market offerings by companies. If the internet was a catalyst for some of the more major servitization projects in recent history, AI perhaps is a further catalyst for even more servitization. Servitization as a strategy creates a low barrier of entry for companies to start exploiting a new technology since their fundamental strategic position doesn’t shift as such.

It should also be noted that extracting value from an external technological innovation such as AI relies heavily on the companies’ capability to extract that value and refine the innovation into something that is within their own scope of business and operations, as discussed above. Cohen and Levinthal (1990) tie this capability closely to something they present as the absorptive capability of the organization. This is a function of the knowledge and readiness within the organization to understand and exploit new technological innovations. Organizations can invest in this absorptive capability via increasing their R&D spending and in the case of particularly knowledge-intensive information or, in the language of the authors, information that is “more difficult to assimilate” which one could argue that AI falls into, R&D spending is especially important and effective in building absorptive capacity. The authors also note that the level of difficulty in assimilating the information is closely tied to the question of how targeted the information is to the firm’s particular needs. In the case of AI, we are looking at a very general yet powerful technology which is not particularly targeted for needs of any one company but rather can be thought of as a utility in the same vein of electricity or the internet. One peculiarity of AI as a technology is that it, by itself, does more or less nothing. AI is more akin to an internet package protocol or a utility like electricity or perhaps indeed, the internet itself. A bank will not gain additional value to its business from just having some tens of thousands of lines of AI code sitting on its server: it has to come up with a solution for utilizing the AI and having it contribute to its own process of value creation and core business strategy.

Leonard-Barton (1992) illustrates the challenges that these types of situations create when she talks about the core capabilities and the core rigidities of an organization and how they are curiously intertwined. On one hand the core capabilities of an organization enhance innovation from new product development but on the other hand they also simultaneously inhibit it. According to the author, excellence in the dominant discipline of a company may help it to implement new product designs and innovations that are not a part of its core knowledge domain by simple “brute-forcing” their way through the problems using their dominant discipline know-how and prowess, which certainly may be one way to approach AI as well. Technical literacy may also play a part in creating new types of applications from novel technologies. Companies with a high level of technical literacy can leverage it to internally test and assess their ideas, while those without it are left to understand them only from exposure to the market.

Furthermore, Leonard-Barton (1992) argues that the existence of core capabilities in essence means that there are capabilities and knowledge domains within the company that are not considered as being part of core capabilities but rather as less dominant disciplines. The problem arises when these less dominant disciplines are needed to facilitate the adoption, exploitation or innovation around a technology that arrives from outside of the core capabilities of the company. This may prove to be surprisingly tricky as these less dominant disciplines more often than not receive the label of being less prestigious within the company. The author found out that the severity of this paradox was dependent on how misaligned the new product development project was from the company’s core capabilities: the more misaligned the projects, the greater the paradox. A similar conclusion is also presented by Christensen and Bower (1996) who note that stumbles of established companies during times of technology disruption are often attributed to a failure of technology adoption, but it is more often than not a failure of strategy change. The question of what type of AI utilizations companies build and how they fare may be indeed largely dependent on managing the paradox of operating outside of core capabilities but yet still drawing strength and knowledge from them and being able to facilitate strategic change.

Danneels (2002) discusses different competences that the firm is required to have in order to facilitate product innovation and the effect of the competence type to the type of the product innovation that ensues from the situation. For this thesis, his model, depicted in figure 1, may be fruitful to interact with and examine closer. Danneels argues that essentially the strategic form of new product development can be seen as either exploitation, where the firm leverages assets it already has (customer data, technological know-how, marketing experience, etc.) or exploration, where the firm goes into new territories it has not yet visited and as such withstands a certain amount of risk and unpredictability that comes with such actions. Especially interesting are the hybrid versions of exploitation and exploration, found in the upper-right and lower-left quadrants of the matrix presented at figure 1. In those situations, the company either appeals to an additional, novel customer segment by exploiting a technological competence it already has (exploiting technology and exploring customers, the lower-left quadrant of figure 1) or builds additional technological competence

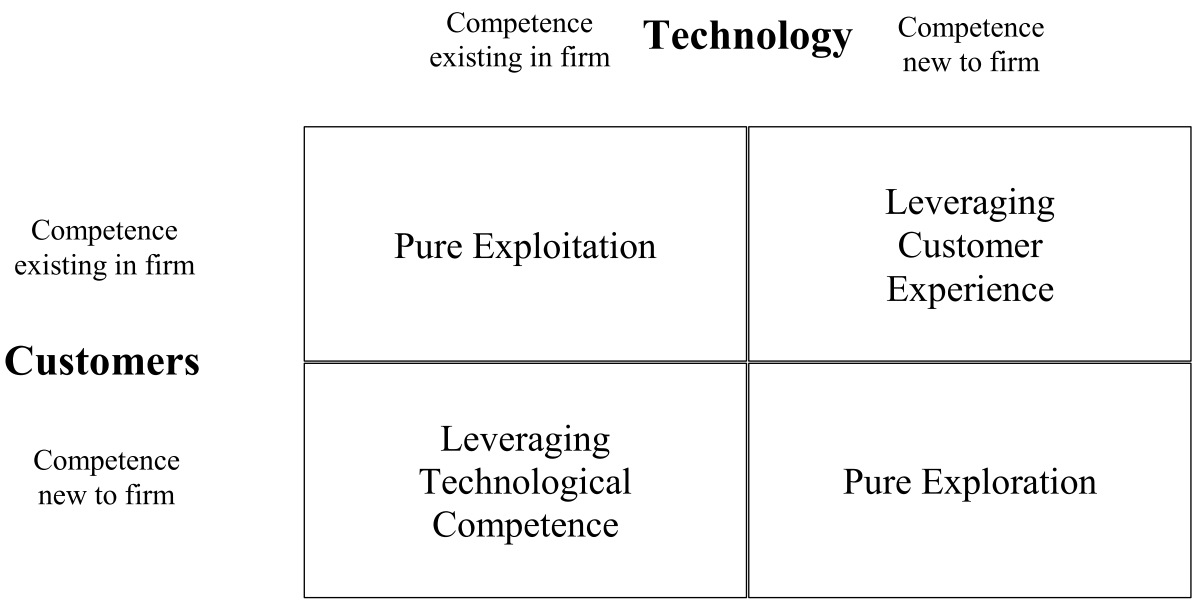

Figure 1: *Competence-based new product typology (Danneels, 2002)*

to answer, understand and cater to the needs of its current customer-base (exploiting customers and exploring technology, the upper-right quadrant of figure 1). It is very likely that companies who are looking into utilizing AI, or any other novel technology for that matter, do retain some sort of a crutch when walking into, new, relatively unexplored territory. That crutch can differ from company to company: certain firms have a large base of technological know-how that they can leverage to gain new customers and others may have a deep level of understanding of their current customers which they can serve even better with technology.

Danneels (2002) also discusses something he presents as “second-order competences”, which he defines as “[...] the ability to identify, evaluate and incorporate new technological and/or customer competences into the firm, i.e., a competence at explorative learning by exploring new markets or exploring new technology.”. He sees them as higher-level competences that are required to apply and understand first-order competences, such as technological or customer competence. In an illustrative example he interviews a new business development manager from a company who states that essentially every company in the defense industry saw the need to diversify their business into commercial applications as well. However, most failed. According to the informant, this was due to lack of marketing prowess and understanding the new type of relationships and dynamics that are required in the new type of marketplace that the firms extended to and, more specifically, the ability to develop those very capabilities. This is also in fact echoed by Leonard-Barton (1992) who notes that an often overlooked and ignored domain of core capabilities is the value assigned within the company to the content and the structure of knowledge, means of collecting that knowledge and controlling it. By this, she is referring for instance to the question of how valuable knowledge that is not considered to be in the core domain of the company is considered within a company: An explicitly engineering-oriented company may not see the benefit and the value of marketing-related knowledge and know-how, and naturally vice-versa. With something like AI, as was previously established, this becomes exacerbated as AI-related know-how is not necessarily the main knowledge domain of any company except companies developing AI itself. Despite of this, the resource investments into AI must be argued for somehow in the companies that are willing to make them. The larger point that Danneels (2002) makes in his paper is the fact that new product development processes and technology exploitation not only draw on, but also develop firm competences. Competences, he notes, have to be continuously renewed in the face of change and product innovation is one potential tool for that.

2.5 Technological framing and business decisions on AI

While primarily this thesis is more interested in the *whats* of AI utilization in business than necessarily the *whys*, this is still an important question to consider. Suffice to say, strategic business decisions on technology utilization do not happen in a vacuum and are not done by actors who function like pocket calculators. Rather, there are technological and political agendas that affect how humans in organizations craft arguments, decide on which R&D to pursue and what is even considered to be progress (and consequentially, what is not). Dosi (1982) called these forces technological paradigms which have powerful exclusion effects: if and when the attention of the organization and its R&D operations are focused in some specified, precise directions, whether it be AI or something more abstract like "digitalization", they essentially become blind to other technological possibilities than the one that is the set agenda, the paradigm in this context. As mentioned, the technological paradigm also more or less defines the idea of contextual technological progress. This simply happens due to the technological paradigm covering the applications of that particular technology, its materials, its key trade-offs and other measures. Within the context of AI, this is rather easy to illustrate: If the technological agenda of AI is to build the most human-like virtual assistant in the world, the agenda favours such features as relative infallibility, trustworthiness, mastery of natural language and ease of use and places less importance on features like raw processing power and, say, image recognition. Progress is then defined as progress within the parameters of a particular paradigm, not as any progress. Dosi's argument is, understandably due to its age, of very focused on physical components and hardware, but it still serves as a valuable entry point to the discussion of technological trajectories and the fact that technological progress and development is a humanistic endeavour with aspects of power relations, politics and subjectivity like any other humanistic endeavour. Clark (1985) also seems to agree, noting that all designs, which technologies are a part of, have some sort of a design hierarchy embedded within them, which in turn means that various functional parameters of a given design are of unequal importance. One parameter sits at the apex of this hierarchy, essentially dominating all levels below it. Clark refers to this parameter as the core concept, a parameter that sets given conditions for all the other parameters to deal with. A practical example of this would be the automobile engine. The engine as we know it today went through a heavy initial design process as the fuel source was still very much up in the air during the early days of automobile design. As gasoline was selected as the fuel source, it created a very different design agenda for the engine than if steam or electricity would have been chosen instead. In an entirely similar fashion, choosing robust ethics as the central design parameter of AI systems creates entirely different design implications and technological trajectories than if saving the maximum amount of money is chosen.

Orlikowski and Gash (1994) introduce us to the idea of technological frames and their effects on organizations' and individuals' relationship with a given technology. According to the authors, the concept of a technological frame can be understood essentially as a collection of assumptions, expectations and knowledge that the use to understand technology in organizations. The frame can be thought of as the interpretation of a technology from the perspective of a given stakeholder. Furthermore, these frames vary from group to group and because interpretations of something that is thought of as being clear-cut in a positivist sense ("Well, E-mail is E-mail! What is there to interpret about it?") are rarely discussed and compared, the frames can be a major source of conflict because of the misaligned expectations and assumptions they produce.

In their study, Orlikowski and Gash (1994) noticed that different employees of the same company indeed had wildly different understandings of the same technology in three different domains that were established to characterize these differences: the nature of the technology in question, the interpretation of the technology strategy of the organization and people's understanding of how the technology in question will be used in day-to-day use. Furthermore, the researchers saw that the frame of the employee even affected the KPIs that the employees based on the technology. The more technology-minded employees tended to refer to the adoption rate or the operation of the technology as their main point of a KPI, even though previously they stated that the technology provided business value to the company and was valuable because of it. The main point of this research is to point out that in order to interact with a technology people must first make sense of it. This sense-making, however, is highly individual and subject to a high amount of variance within an organization. The modes of utilizing AI, or the archetypes of AI utilization, then are reliant on this sense-making process and the frames that it casts on the technology. If, for instance, a business manager or equivalent actor casts AI in a frame that deems it "value-adding" or "good" or perhaps "important", then AI would ostensibly receive a higher share of resources in that organization than something that the same manager frames "a waste of time" or "difficult to understand". This is of course a very crude and simplified example, but the logic applies nonetheless. Technology frames matter and they are something that is critical to understand when looking at a way an organization deals with an incumbent and/or uncertain technology. Each decision, goal and KPI is influenced by a technological frame of some actor, conscious or not. This is to say that the artefacts of these frames do not exist in a connectionless vacuum where they were put by the hand of God, but rather that they are products of interpretations of technology and business.

The literature on technological frames does also touch on the topic of technological trajectories as an effect of technological frames in organizations.

Kaplan & Tripsas (2008) expand on the idea of technological frames by introducing the idea of cognitive technological frames to the technology life cycle literature, positing that framing activities (or in the case of this particular study, "cognitive lenses") within an organization affect what it considers a dominant design. According to the authors, a technological frame

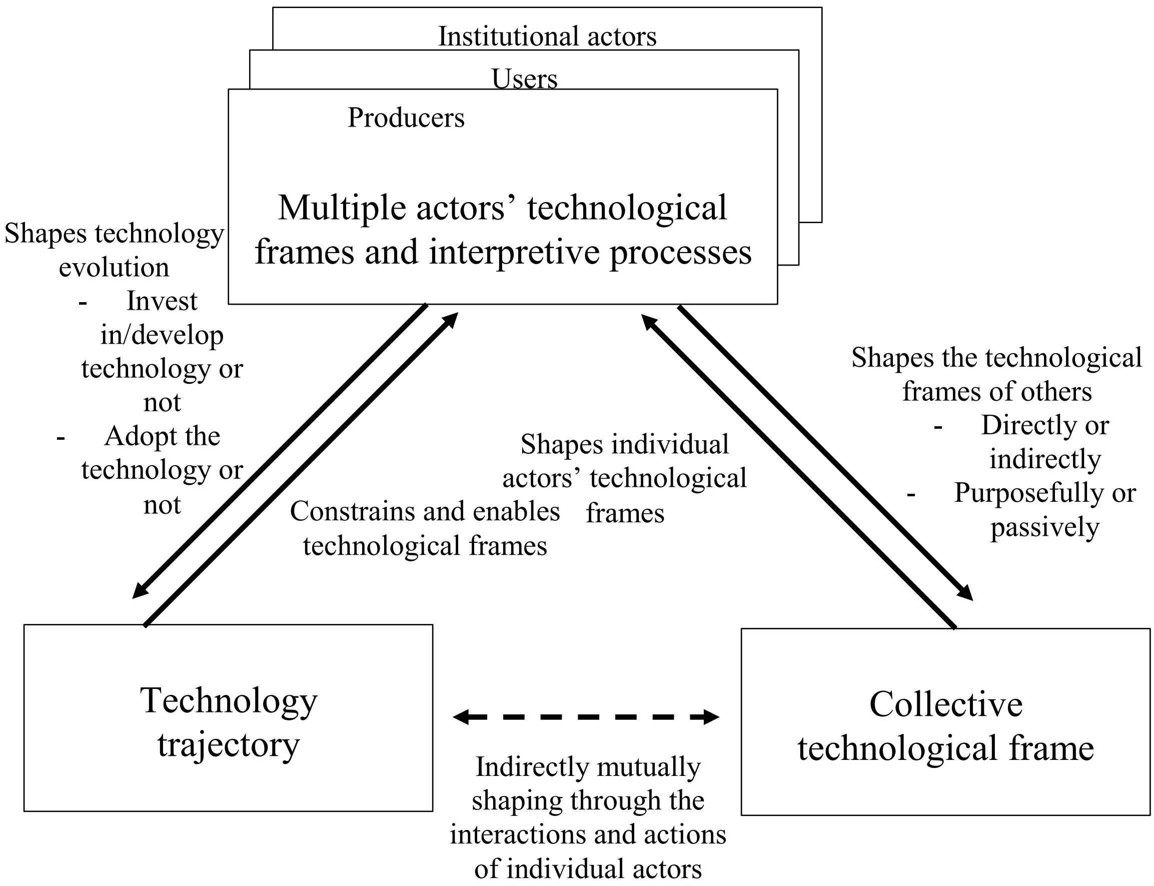

***Figure 2:** A cognitive model of technology trajectories (Kaplan & Tripsas, 2008).*

can even be so dominant and unescapable in the day-to-day reality of the company that it can cause it to miss new technologies as they emerge simply because they may not fit the existing technological frame of the company. Kaplan and Tsipras also introduce us to the idea of bi-directionality when thinking about the influence of individual technological frames and the actual trajectory of the technology in question, as well as the "collective" technological frame, the technological frame that is collectively shaped as a result of the competition of different frames brought forward by various different actors in the framing process (figure 2). This collective frame is certainly politically tinged: framing can be used as a vehicle for forwarding one's own agenda which can then be attempted to insert into the collective technological frame thus advancing the political goals of the original framer. This is something to keep in mind when looking at the discussion on AI, which, as we previously established, ranges from fervently positive evangelism to fearful doom-saying.

An even yet more interesting is Kaplan & Tsipras' idea of the actual technological trajectory of the technology getting affected by both the technological frames of the individual actors and the collective technological frame and then the trajectory reflecting back to those frames to further inform and shape them. This is essentially why finding out about the archetypical utilizations of AI is so critical at this stage of its lifecycle: by finding out what the companies who hold major amounts of knowledge and/or data related to AI are doing in the field of AI, the actual technological trajectory can be deduced, or at least a portion of it. Similarly, looking at the archetypes will give us an idea of what the collective technological frame for AI is and how that perhaps should be addressed on a policy and communications level. The model should not be understood, however, as something that posits technological trajectories are all about optics, lobbying and marketing. According to the authors, technological frames influence actors' technical choices, which are directly the mechanism that drives the actual technological development of the techonology. Producers invest in it or not, users adopt it or not and institutional actors support it or not. In this way, the frame influences the outcomes and as earlier established, the outcomes influence the frame.

2.6 Dominant Design

An important stream of literature to discuss in context of this thesis is literature on dominant designs, the idea that when a technology is fermenting many designs compete for the status of a dominant design, which will emerge as a *de facto* standard for the industry as the "winner" of the competing designs. This research stream often examines the tension between a new technology (such as AI, in the case of this thesis) conflicting with an existing business model or an organizational design which it naturally has no explicit place in, as it is new. Indeed, Murmann and Frenken (2006, p. 945) go so far as to say that "One can interpret the entire history of dominant design research as an attempt to find a theory that would map technological changes to changes in the industrial organization of firms and markets." This alone makes this stream of research worthwhile to at least understand in order to contextualize our AI archetypes in relation to the idea of dominant designs rising to the top in a particular industry or within a technology.

Abernathy & Utterback (1978) establish in their landmark study of this stream of research that new innovations which require reorientation of the business goals of the company or the processes of the business tend to originate in units that are not devoted to a specific production system as the specific production system itself is grounds for dismissal of this innovation. The authors liken these types of innovations to an entrepreneurial act within the company and they are often associated with emerging needs of the end customer or a new way of meeting existing needs. Furthermore, these innovations tend to originate in units that are located close to affluent markets with universities or research institutions and entrepreneurially minded financial institutions. What's more, Abernathy & Utterback establish that when a major product innovation first appears, the performance criteria that it is valued upon are often vague and not well understood. This is certainly quite well reflected on the general discourse on AI, especially the business and public discourses (see chapters 2.2.1 and 2.2.3 for details). Perhaps it could be understood through the lens acquired from the dominant design literature that the lack of generally understood performance criteria of AI technologies is not a shortcoming but rather a feature of the discourse, perhaps driving it towards a shared understanding of those performance criteria.

What is the reason for dominant designs existing? In the context of AI utilizations, this is a question that is quite interesting from the perspective of AI utilizations, as it can help us to understand the circumstances that have led to a particular archetype forming or, better yet, understand the future circumstances that may produce new archetypical utilizations of AI, or any technology that has a design element for that matter. According to Murmann and Frenken (2006), the scholarly discussion on dominant designs has produced five reasons why a dominant design is born in the first place: 1) A dominant design represents the best technological compromise among the different functional characteristics of the technology, forcing imitation from the competitors. 2) Dominant design is born due to only economies of scale that can be realized with standardized products. This means that essentially the design that initially acquired a lead in the market will emerge as dominant. 3) Dominant design is dependent on network externalities, a situation where the value of adopting a technology depends on the number of users who have purchased a compatible technology. Computer platforms have traditionally been seen as one of these. 4) Strategic maneuvering such as coalitions, R&D collaborations, pricing and licensing may cause a firm to achieve the status of a dominant design. 5) A fifth line of research understands dominant design as something that emerges through a combination of sociological, political and organizational dynamics and not because of market conditions. As it often is, the actual answer most probably lies somewhere in the cracks of these five, taking elements from each in varying degrees. In the case of AI, it is worth giving particular attention to the third dominant design typology, network externalities. Much like it's distant cousin, the internet, AI is to some degree dependent on the methods of using it and how big of a network effect it can muster. This is simply due to the required troves of data that are needed to train and properly test algorithms. However, we may be rapidly heading to a chicken-and-an-egg -situation with the network externalities of AI: AI utilizations that produce business value require significant data resources that are both wide and deep. However, these data resources require investments from the organizations. In order to invest in large-scale data gathering systems, the organizations would most likely want to know the value of the investment, the expected rate of return. However, this is tricky to calculate since it would require a dominant design of AI utilizations to exist and be well documented. And so, the circle begins anew.

While certainly relevant, this stream is not without its shortcomings in the context of this thesis. Dominant designs are often understood as products or technologies, rather than business models or ways of utilizing technology. In other words, viewed through the literature on dominant design, the conversation about AI becomes a conversation about the styles of algorithms, the specific designs of neural networks and machine learning paradigms and not so much a conversation on how they tie into business strategy and objectives, and how the technology should be utilized. This is not ideal for a thesis that is explicitly interested in the business implications of AI.

This is not to say that the scholarly discourse on dominant designs is useless: it contains observations of many dynamics that are also present when discussing strategy, business models and value creation mechanisms. As such it is important to consider and gives a valuable contribution to the theoretical framework of the thesis but cannot support it alone as its origins are so heavily rooted in product and technology design. For this, we need to think of the archetypes as different business models within the company, understanding the product units in which AI is used as business units with perhaps diversified business models, which in turn contribute to the overall business model of the company. In the following section, I will examine the (relatively) nascent but very active academic discussion about business models, the effects of business models and their relationship to innovations, which I consider technologically and economically feasible AI to be.

2.7 Business models and AI

Business models are powerful, informationally dense tools for understanding why and how companies do the things they do, or as Baden-Fuller and Morgan (2010) put it: “The concept ‘business model’ can be said to define the business’s characteristics and its activities in a remarkably concise way, in other words, in a way that matches the generic level that defines a kind or type of behaviour (neither too general nor too particular in its detail) but that also suggests why it works, because it embodies the essential elements and how they are to be combined to make them work”.

As a topic of conversation regarding profiting from innovations and new technologies, the idea of business model of the company and/or the mode of utilizing the innovation is relatively novel. Teece (2010) attributes this to the roots of business theory and strategy as an offshoot of classical economic theory. Teece posits that the curious absence of literature on business models stems from the fact that in much of the literature on economics and by extension business, markets solve problems that are actually solved by business models in the real world. The economic theory assumes that if and when markets are perfect, all products will find their buyer naturally since their value proposition is so explicitly clear to the buyer, who in turn has perfect understanding of their wants and needs and what might be the correct way of proceeding with their own business, for instance. Furthermore, classical economic theory assumes perfect symmetrical information to exist in markets, which is a far cry from the reality of digital service business. The value of innovations can be rather difficult to understand right off the bat as they contain things like dynamic network effects, open innovation platforms and other components that may not do much on their own (compared to something like, for example, a tomato, where the utility is crystal clear: it is a tomato and you as a consumer either want it or not) but they can enable exponential revenues through platform business models. This ties back to the conversation about AI as a utility that was discussed in chapter 2.3. Utilities like water or electricity do not add value because of their explicit, inherent value but rather because of their utilizations, the problems that can be solved by using them in novel ways. They act as enablers and mediums for delivering value. This is remarkably similar to the way that AI functions: as an enabler for companies with huge amounts of existing data and need for decision-making at a massive scale. A factory that was driven by machines powered by steam fundamentally produced a similar output as a sewing shop, it just did so at a vastly different rate and with a very different cost and profit function. However, this change paved the way for larger, more radical innovations in industry further down the line. In a similar manner, AI has the capability of instigating radical change, but the vehicle for it will most likely be something that looks quite conventional, i.e. shifting the scale of processes that are already quite well understood.

A business model, according to Chesbrough (2007), essentially performs two functions: value creation and value capture. These break down further, in that the value creation function defines a series of activities in a way that they create net value throughout the various activities. The other part of the equation, capturing of the value that is created, simply put earns a profit from the activities defined in the value creation function. Three years later, Chesbrough (2010, p. 354) crystallizes his view even further: "Companies commercialize new ideas and technologies through their business models." This sentence packs quite a lot of meaning, however, as he explains. According to Chesbrough, business models matter because they have such powerful effect: the same technology commercialized through two different business models will yield two different results, not to mention that technology itself has no value whatsoever. The value that is bound to that technology remains latent until it is commercialized with a business model.

This Chesbroughian understanding of a business model suits the discussion on AI exceedingly well, as it is a versatile family of technologies that behaves much like a tool to unlock value-creation potential in the firm through more conventional endpoints. While it is in many scenarios easy to understand the value creation of AI activities, the value capture might be a significantly more challenging to articulate at this point in time. One reason for this may indeed be the heavy investments often (rightfully) associated with AI: The need for data scientists, computing power and large amounts of data resources put a significant amount of pressure to the value capture function of AI utilizations in companies even when it is easy to see the value creation part of the business model proposed by the archetype of AI utilization.

Other definitions of the concept of business model do exist as well and are rather important to discuss in order to understand the holistic nature of the academic conversation on business models. Coming from a rather different perspective than Chesbrough earlier, Zott and Amit (2010, p. 216) conceptualize the business model as "a system of interdependent activities that transcend the focal firm and spans its boundaries." In practice, this is an approach that is from the deeply pragmatic end of the spectrum of definitions of the topic: The authors understand the business model as the consequential situation that arises from the decision of how to engage in business. Here the actual question of delivering value and capturing value is only a small part that co-exists with questions about the set of activities required to deliver and capture the value and the resources and capabilities that are required to execute those sets of activities, either within the firm or beyond it, in co-operation with partners, suppliers and customers. Another way of approaching the business model as a concept comes from Baden-Fuller and Morgan (2010) who assert that a business model essentially has three roles: a means to classify and describe businesses, a site for scientific investigation and a recipe for creative managers. Of these roles, the first and the last ones are especially interesting from the perspective of this thesis, both of which will be further discussed later. Demil and Lecocq (2010, p. 227) shift the focus of analysis to a further macro level by presenting that while generally the business model can be understood as the "articulation between different areas of a firm's activity designed to produce a proposition of value to customers", the discourse on business models generally divides into two different uses of the term. On one hand, the business model is used as a kind of a blueprint for the coherence between core business model components. On the other hand, there is the approach where the business model is a transformational tool used to address change and innovation in the organization, or the model itself (referring to a more instrumental idea of the business model).

This idea of a business model as a transformational tool that can be used to highlight components of innovation and change is very intriguing, as we shall see later on. Nearer to the end of the spectrum of understanding business models as purely a tool for managerial strategy discussion is McGrath (2010), who sees business models as appealing units of examination because of their very nature as a material artefact of the strategy. Modelling, according to her, is a useful approach to figuring out a strategy as it suggests on a purely semantic level something that has to do with experimentation, prototyping and a job that is never quite finished and always in flux.

This type of discourse about the fundamental baseline philosophies of doing business is exactly why business models will be the main avenue of analysis and understanding when interpreting the empiric data (see chapter 3.2) of this study. While discussion of technological diffusion, exploitation, technological framing and dominant designs is interesting and important in order to understand the entire picture painted by the data, the business model speaks the language of business: if a technology can't justify its existence to the decision-makers in the company its prospects of survival are not great. While there are many different definitions of what a business model exactly is, this is not a detriment to the concept. On the contrary, it underlines its connectedness to the uncertain, ambiguous world of novel technology exploitation and acquiring constant competitive advantage.

The business model literature as a backbone for the framework used in describing the archetypes of AI utilization gives as a plethora of tools to understand the justification, the reasoning and the practical value creation mechanisms of these archetypes, which will then hopefully serve as meaningful templates for businesses who are on the verge of adopting AI technologies. However, it should be noted that looking through the company and its activity networks through a business model lens is far from a magic bullet that solves everything when it comes to technology shifts. Tongur and Engwall (2014) discuss a phenomenon that's known as the "business model dilemma", which essentially is a situation that arises in incumbent firms (of which the two end users of AI solutions interviewed in this study definitely are) when a technology shifts presents itself in a given industry. The incumbent firm can at this stage either choose a strategy of technological innovation or a strategy of servitization in relation to the new technology shift. Both present ambiguities: a strategy of technological innovation is often ambiguous in its value proposition and value capture functions while a strategy of servitization can be quite ambiguous when it comes to value creation itself. The point here is fundamentally this: while business model research literature provides a large array of tools for analysis, it doesn't provide any answers per se. These answers are something that companies must discover on their own through experimentation, analysis and iteration. This is to say that while business model literature is a great well of resources for lenses of analysis, in this thesis it is not thought as a one-size-fits-all solution for all woes and uncertainties related to AI, or any new technology for that matter.

2.7.1 Business models as a focal point of this study

As this master's thesis is interested in the practical ways that businesses are utilizing AI in 2018, it is imperative to attempt to document those ways through a medium and language that is understandable and relevant to both business leaders and researchers. Chesbrough (2007) also notes that shortening product lives mean that superior technological performance can't be solely relied upon to earn a satisfactory profit before it is commoditized: this places a higher pressure on the business model to deliver the benefit from the innovation to the company. Teece (2010) echoes this idea by noting that every new product development should also be coupled with a business model development which serves as a way of defining the new product's strategies of capturing value and going to the market. This is the very question that the utilization archetypes attempt to answer: What are the go-to-market strategy, the reasoning and the value capturing mechanisms of a given unit of AI exploitation in 2018. As the business model literature deals very explicitly with questions of strategic ambiguity it suits very well in this endeavour: the practice of creating, maintaining and tweaking a business model is the practice of understanding and articulating technology exploitation strategies and turning them into customer value, which in turn will be captured by the company and, at least in the best-case scenario, is turned into shareholder value. This is the reasoning for why business model literature is so closely examined in this master's thesis, even though creating AI utilizations may or may not alter the actual business model of the focal firm. The sense-making process related to turning a new piece of technology into shareholder value is similar enough for our purposes.

In addition to this, it might be added that focusing on business models and the activity systems related to business models is a similar approach as the one taken by Bocken et al. (2014) in a paper that served as a central inspiration for this study. In the paper, the researchers studied archetypes of sustainable business models and thus used the concept of business model as a central organizer of their worldview, just as it shall be used here. This is mentioned to avoid potential confusion caused by "business model" as something that is perhaps most often understood as a firm-level undertaking and concept, rather than a product-level concept. While this may be true, it also can be used to examine more granular phenomena, as individual business units and products may have their own individual methods of value creation and capture that are independent from the firm-wide methods yet compatible with them.

Lastly, this approach is chosen because of the way it uniquely fits the logic that AI innovations operate on. As already earlier established, AI itself is a collection of different technologies and logics, that enable an endless array of innovations, both incremental and radical. In this way it's markedly different than something that is purely a technological innovation, like a certain type of software, an algorithm or a touch screen. As already noted, AI is closer to a platform-esque, radical shift in business logic that affects businesses on a structural level. Innovations like this are things like the internet, electricity, steam power and the like. This also makes it particularly interesting to look at AI through business models since each industry and each company in that particular industry may have a slightly different way of exploiting the possibilities that are presented by the feasibility of AI as we understand and know it. Interpreting each AI utilization as a business model with a certain way of creating and capturing value provides us with uniformity across industries, cultures and companies and maintains a similar level of granularity throughout. This line of reasoning is also echoed by Baden-Fuller and Haefliger (2013) who posit that a given technology does not operate in isolation from other technologies and it is this interoperability that is required to create the intended value. According to them, recent introductions of sophisticated IT and platform technologies have made this very relationship even more dynamic and uncertain.

2.8 Business model as a tool for decrypting the company

In the knowledge domain of innovation management two ideas characterize the extant research on business models: Companies commercializing innovative ideas and technologies through their business models and the fact that the business model represents a new subject of innovation which complements the traditional subjects of process, product and organizational innovation, involving new forms of cooperation and collaboration (Zott, Amit and Massa, 2011). In many regards, this thesis seeks to decrypt the business decisions made by companies who have decided to in one way or another utilize AI in their business. While the overarching, top-level aim is to find out and verbalize the archetypes of AI utilizations, in practice this means understanding the business models that these archetypes, and by extension, business units rely upon and by that extension entire companies also rely upon. The business model of a given AI utilization instantly tells a vivid story about its origins, the market situation it seeks to address, the resources needed for it and what is the strategic justification for it. This is why the approach of describing the archetypes will be heavily reliant upon concepts, language and ideas that have emerged from the literature on business models: they communicate large amount of information in a very efficient manner, information that might be too sensitive to explicitly verbalize or has never even necessarily been explicitly verbalized.

This idea of business models as tools for typologizing companies and business behavior is also echoed by business scholars. Baden-Fuller and Morgan (2010), as established earlier, see the business model as a recipe of the company, something that provides a set of rules that can be expected to produce a particular kind of outcome. At first, this may sound naïve and straightforward: after all, companies cannot be replicated by just anyone solely on the basis of a verbalized business model. Neither can recipes, for that matter. A recipe requires ingredients, resources, a certain standard of working conditions, not to mention a tremendous amount of tacit knowledge about how cooking works, how certain ingredients pair and behave with other ingredients and so on. What's more, recipes are not strict step-by-step instructions, but rather as documents open to interpretation, experimentation and variation. Baden-Fuller and Morgan note that much like recipes using cooking, this variation will change the outcome and its resource/ingredient requirements as well.

According to Teece (2010), a business model reflects management's hypothesis about what customers want, how they want it and how the enterprise can organize itself to best meet those needs, get paid doing so and make a profit on top of that. This is more or less the set of questions that is critical about an archetype of AI utilization: What is the business challenge it is addressing, how is it addressing it and what is needed to be done for executing it. The monetization is taken as a given: Generally, an organization does not partake in activities that do not in one way or another provide a net profit. Whether this is in the long or short run, by investing in capabilities or reaping a rapid profit, directly or indirectly, are all choices that organizations make themselves according to their own relative market situation. Christensen (1997) also notes that it is typically not true that when disruptive technology shifts happen that the challenge would be a technological challenge. Rather, firms that were most successful in commercializing disruptive technologies were those that understood the challenge as a marketing challenge where the task was to find a market that would fit the technology, and not the other way around. This is to say that examining business model decisions, which themselves are manifestations of marketing strategy, is a fruitful approach in order to understand AI utilizations. Another viewpoint to the discussion on understanding what goes on under the hood of companies is provided by Zott and Amit

(2010), who provide a perspective to business models that focuses on business models as the decrypting tools of systems of activities. An activity is something that is the engagement of human, physical and/or capital resources of any party to the business model in order to serve a specific purpose toward the fulfillment of the overall objective. An activity system then, is a set of activities within the firm that are understood to be interdependent of each other. The activity system may transcend the firm and span its boundaries through networks and other dependencies, but it is still a system that in the end of the day contributes to the firm's success.

This view of business models as complex systems of activities that manifest themselves into action is a similar to the one presented by Tikkanen et al. (2005), who present business models as processes encompassing the entire organization, stemming from the very material resources of the organization (such as the company's network of relationships, operations embedded in the business processes of the company, strategy and structure and finance and accounting concepts of the company) which manifest themselves as the belief system of the company (comprised of understanding of company reputation within the industry, the conventions of the industry formalized in industry recipes, boundary beliefs of the business and ontologies of products), which ultimately result in actions taken by the company, creating business model evolution. While this may seem convoluted, it's actually quite clear-cut and well-defined, essentially understanding the company as an input-output system, with managerial cognitions processing the inputs into outputs. This is highly relevant from the standpoint of this thesis as the AI utilization models, in the end of the day, are just materializations of managerial cognitions on AI, as interpreted by myself. While the framework by Tikkanen et al. (2005) can feel outdated due to its strong inward orientation and lack of consumer-centricity, it still represents a valuable addition to the conversation of understanding companies through their business models.

On a more concrete level, however, the activity system school of business model thinking is perhaps embodied in a clearer fashion by Zott and Amit (2010), when they talk of the ways of shaping and understanding activity systems as characterizing them through their design theme, a central driver that details the system's value creation mechanism. They present four of these drivers: 1. Novelty (Adopting innovative content, structure or governance), 2. Lock-In (Building elements that retain the business model stakeholders), 3. Complementarities (Bundling activities to generate more value) and 4. Efficiency (Reorganizing activities to reduce transaction costs). These themes serve to understand what is the central mechanism that orchestrates and connects the different elements of an activity system. In this thesis, they serve as typologizing tools that create further understanding of different archetypical AI utilizations and their components. Recognizing the underlying ideology of a model of utilization through a tool like this can be very helpful in understanding whether the archetype of utilization can be used in a different organization and/or situation or not.

Besides the drivers for value creation, for the analysis AI utilization archetypes the idea of a "deep truth" is highly salient. Teece (2010) discusses at length about this concept of the deep truth. According to him, business model pioneers often possess or develop an understanding of a "deep truth" about the fundamental needs of the consumers and how competitors are not fulfilling those needs, and of the technological and organizational possibilities for improvement in this regard. This idea is critical from the standpoint of AI, since it takes a holistic view of the business and the customer, rather than being too obsessed with technologies or certain resources. Rather than asking "What should we do with AI for our customer?", the deep truth concept asks "What should we do for our customer?" and then evaluates *how* the answer to the first question should be handled. Looking at different AI solutions through the lens of this thesis, we can assume that each of the organizations who implementing the solutions have at some point asked a version of the question that has led to the deep truth, which in turn then has been answered by using technologies that can be classified as some form of AI. Inferring this deep truth from the interview data should be extremely helpful for companies and scholars alike in the future to understand in what kind of deep truth situations certain types of AI utilizations emerge.

2.9 A framework for representing archetypical utilizations of AI

For the purposes of actually representing the findings of this thesis, a composite model was built using different elements that were discovered from the literature on innovation diffusion and exploitation, technological framing, dominant designs and business models. Of these domains of research, business model literature was studied especially closely, as the business model is seen as having an especially important role in unlocking the value potential of embedded in new technologies and converting it into market outcomes (Zott, Amit and Massa, 2011).

Figure 3 shows the blank template for a given utilization archetype, to be used later in this study on the basis of the interview data. This model has been built as the composite form of several theoretical concepts discussed in this chapter. Its objective is to model an archetype of AI utilization on a level that strikes a balance between abstraction and detail, of operational, tactical and strategic granularity. The composite model is crucially important for the study, as it is the primary and the only vehicle for expressing the materiality of the utilization archetypes that rise from the empirical data. It is explicitly focused on the *business* effects of AI, or any technology for that matter, as this thesis is also explicitly focused on questions of innovation management, technology strategy and value creation and capture.

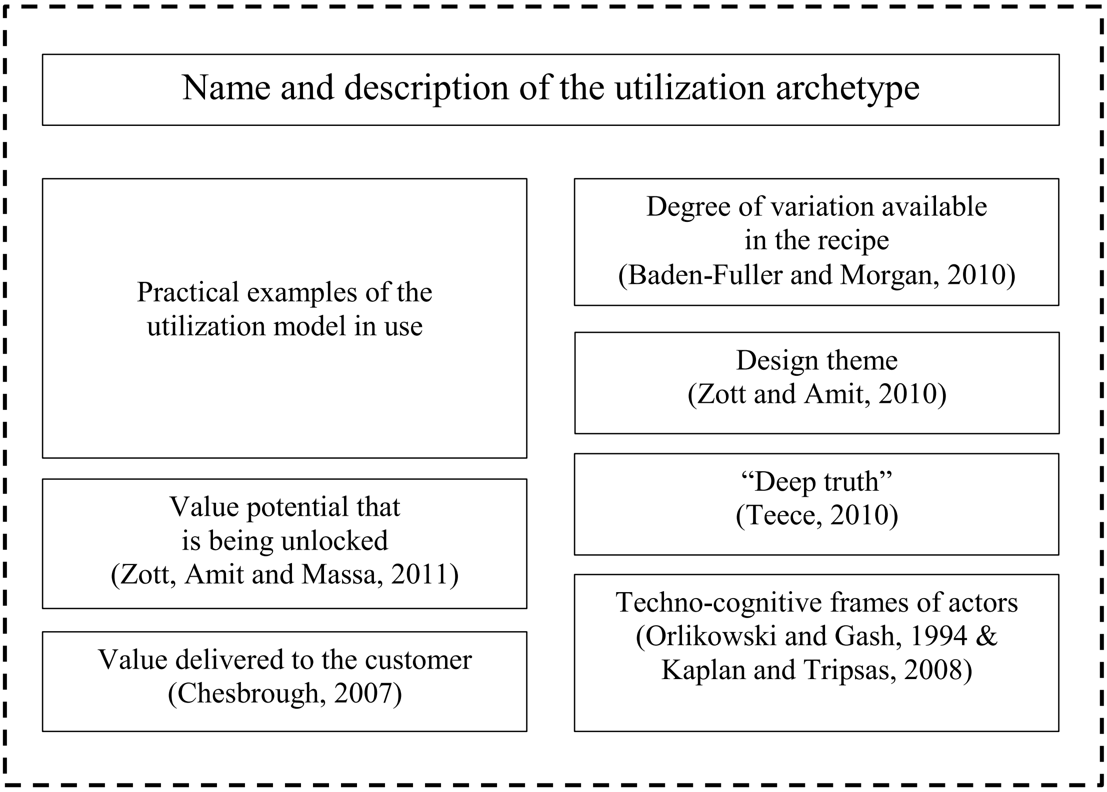

Figure 3: *A composite model of a utilization archetype*

The model begins by stating the name and the description of the utilization archetype. The name, it should be noted, is an arbitrary identification aide devised by the author. Moving anti-clockwise, the next element is a collection of practical examples of the utilization archetype in use. These are used to illustrate the practical market outcomes of using the archetype in question. They are not a comprehensive list of all use cases but rather illustrative and general examples. Below this, there is a description of the value potential that the utilization archetype unlocks in the technology in question, in this case AI. This concept derives from the notion by Zott, Amit and Massa (2011) that business models unlock value potential in technologies. As discussed previously in this chapter, the question of value potential and how it is unlocked is a central topic to business model research especially when it comes to new business technologies. Given that AI has been noted to be a general technology akin to electricity or the internet the question of unlocking a value potential is extremely important and central. One row below this, there is an articulation of the value delivered to the customer on an abstract level. Chesbrough (2007) notes the tension that exists between value capture and value creation and notes certain technologies capture more value for the firm than create value for the customers and vice versa. This segment explores that value that is delivered by the commercialized technology from the perspective of the end customer, as opposed to the firm itself. On the right-hand side, starting from the bottom, there is a description of the techno-cognitive frames of the actors involved. This is an explanation of the sentiment and cognitive framing that the actors who are attached to this archetype generally seem to share. Cognitive lens, as established earlier, is a concept first derived by Orlikowski and Gash (1994) and then further refined by Kaplan and Tsipras (2008) into having more dramatic effects on the trajectory of a given technology. Above it, there is the concept of the "deep truth" as mentioned by Teece (2010) and discussed in more detail earlier in this chapter. The purpose of it is to provide the archetype with a strategic implication, a foundational insight that the utilizations presented by the archetype all share. One row above, Zott and Amit's (2010) design theme concept can be found. This theme will provide the reader with an idea of what is the central activity system mechanism of the archetype. Lastly, the degree of variation in the "recipe" (Baden-Fuller and Morgan, 2010) will be discussed. This degree of variation will give a hint of how elastic a given archetype is for modification of its component elements. This model shall be put into use in chapter 4 as the findings of the empirical data are discussed at length. The value of the model is its capability of condensing a large amount of information into a relatively concise space and imparting managers and scholars alike with a general picture of the situation that is accurate enough to further discuss.

2.9.1 What is the need for yet another business model framework?

A fair question, especially in the context of a master's thesis, would be to at this point to inquire whether the world needs another business model framework for modeling business decisions through their material manifestations, especially as many of these models exist and are highly regarded by both the scholarly and the managerial communities around the topic.

This boils down to two parameters, however, that have to be fixed to a very certain type of position for typologizing AI utilization through the business model literature: granularity and abstraction.

Often, and understandably so, the level of granularity is quite low in this type of literature, meaning that the literature is interested in the business as one large entity, rather than business units, product groups or other components of the business. This is certainly appealing from a managerial perspective, as it provides much more clear-cut answers for the top management than focusing on certain strategic positions in certain business units and product groups. This is intellectually perhaps a somewhat more interesting question than focusing on more granular developments within business units. However, confusing the development of AI utilization in businesses with the development of the entire business would also be erroneous: while AI is an impactful and transformative technology, at this very early stage of feasibility it is important to understand the practical utilizations of it and the thought patterns behind them, rather than speculate the dynamic effects of a singular technology to such an intricate and complex entity as a business. This is why the level of granularity has to be fairly high, in order to understand what the inclusion of AI technologies actually changes in the business and why. This is not to say that we are dealing with non-strategic issues, but rather as a note why the extant literature on business models does not provide with a ready-made solution to analyze the effects of a technology on business thinking, and vice versa.

The other side of the coin is the level of abstraction. Popular models like Osterwalder's and Pigneur's (2010) Business Model Canvas approach the topic from an abstraction level that is in sync with the low granularity of examining an entire company, which is to say that the abstraction level is practical, rather than theoretical or conceptual. This is by no means a wrong way of approaching business models and it is actually probably of much more practical use for start-up entrepreneurs, business managers and other practicioners of business than the one detailed in chapter 2.9, but it is simply too practice-oriented for what this thesis wants to achieve, to detail the archetypical utilizations for an emerging technology (in this case, AI) and the business thinking behind those utilizations.

	Practical — **Abstraction** — Conceptual	
Granularity		
Macro	Osterwalder and Pigneur (2010, p. 44)	Zott and Amit (2010, p. 221)
Micro	Mason and Spring (2011, p. 1034)	Composite model of a utilization archetype (figure 3)

Figure 4: *Comparison of business model frameworks*

Certain understandings of business model are also hybrids in this regard, with a higher level of abstraction or a finer level of granularity, but not necessarily both. Mason and Spring (2011), for example, introduce a model which they use to analyze the recorded sound industry in fascinating detail. Their model is such that it allows analysis on multiple levels using three main elements of the business model (according to the authors): Technology, Network Architecture and Market Offering. This trio of elements is used then to analyze the decisions made by large companies, singular entrepreneurs and business units of companies alike, effectively demonstrating the possibilities of applying business model literature and language to a relatively "micro" level of granularity. However, the model is also quite practice-oriented with its three elements being quite instrumental, rather than something more focused on the thinking behind the decisions that led to the elements being chosen. In a similar manner, Zott and Amit's (2010) model that discusses business models through design themes, which was already discussed earlier, is a highly conceptual approach to business and the strategic reasoning behind business decisions, yet it exclusively sees the unit of business as the firm itself, and not, for example, an entrepreneur, a product or a business unit. The differences of different interpretations of business model frameworks can be seen illustrated in figure 4. The composite model of a utilization archetype that was presented earlier attempts to occupy the zone in the lower-right quadrant of the matrix, combining a micro-level approach of being able to analyze a single product or a business unit with a conceptual mentality where the mechanisms of value creation and capture are highlighted.

While all this may seem as trivial, it is in fact crucially important so as to avoid confusion when discussing the findings of the research in chapter 4. The central reasoning for highlighting the granularity of the unit of analysis is simply the fact that while the business model of a company can be something, individual business units, managers and employees will have their own interpretations of this business model which result into further, self-contained business models within those units. In a case where the focus of the study is on a very novel, emerging technology such as AI, this is highly relevant: the fact that a single business unit is utilizing AI in their operations does not mean that the business model of the entire company is driven by AI, but it can mean that AI is a central component of the business model of that particular business unit.

3 Data and Methods

3.1 Methodology

The empirical part of the study was done through the technique of semi-structured theme interviews in four companies (see chapter 3.2 for more detailed information about the companies and the informants). This method allows the researcher to understand the topic through the actions, experiences and words of people who have worked with the topic and gained a large experience from it. As most of the literature that inspired the methodological perspective of this thesis, this thesis also adopts an abductive mode of inference. Frankfurt (1958, pp. 595-597) discusses philosopher C.S. Peirce's various texts on abduction and reaches a conclusion where "[…] abduction leads us to adopt hypotheses as *working hypotheses*, as worthy of investigation and verification […] abduction is a sort of argument whose function it is precisely to establish the "admissibility of hypotheses to rank as hypotheses."". In this sense abduction is a suitable route going forward when working with novel, unproven technologies and their business implications as this thesis is interested in mapping a relatively new and emerging phenomenon.

According to Eriksson and Kovalainen (2008), while qualitative research interviews do consist of talk organized into a series of questions and answers, they may also resemble everyday conversations in which the distinction between the interviewed and the informant is less evident. This of course may lead to a more natural flow of conversation as the informant might trust the interviewer more because of the relative informality but this is ultimately up to the informant and dependent on multiple other factors as well.

Kvale and Brinkmann (2009, p. 3) define a semi-structured interview as "an interview with the purpose of obtaining descriptions of the life world of the interviewee in order to interpret the meaning of the described phenomena." Building on this description, the semi-structured interview method fits this topic and research question exceptionally well, as the objective is to find out about the archetypes of AI utilization from the point of view of people working on those very same utilizations and understanding the phenomena through the descriptions of the world by the informants of the study. In addition, consider what Brinkmann (2013, p. 21) has to say about the nature of the semi-structured interviews in qualitative research:

"[…], semi-structured interviews can make better use of the knowledge-producing potentials of dialogues by allowing much more leeway for following up on whatever angles are deemed important by the interviewee. Semi-structured interviews also give the interviewer a greater chance of becoming visible as a knowledge-producing participant in the process itself, rather than hiding behind a preset interview guide. And, compared to unstructured interviews, the interviewer has a greater saying in focusing the conversation on issues that he or she deems important in relation to the research project".

This illustrates the value of the semi-structured approach quite well: as concepts such as "archetypes", "business models" or "value capturing mechanisms" can be quite vague and abstract, not to mention the entire field of artificial intelligence itself, it is important in the context of this research that the researcher can freely, yet in a controlled manner maneuver inside the question set and help the informant in this way to express themselves by aiding with definitions, asking probing questions and giving examples. This is echoed by Stephens (2010) who justifies the choice of semi-structured interview methodology by the fact that it provides an opportunity to gain an account of the values and experiences of the informant in terms that are meaningful to them. Furthermore, the agenda of the interviewer ensures that all necessary topics are discussed, while allowing the interviewee to introduce issues that are important to them flexibly to the conversation and without "disturbing the method". This seems to also be the consensus about the method by Eriksson and Kovalainen (2008), who note that the major advantage of a semi-structured interview is the fact that the materials are somewhat systematic and comprehensive, while the tone of the interview is still fairly conversational.

3.1.1 Research design

The research design and the ideology, the basic logical underpinnings of the study, were heavily influenced by Eisenhardt's (1989) arguments for a more fluid, data-driven qualitative research that is willing to grant flexibility for the data to breathe and express itself with a higher degree of veracity and naturality. In her seminal paper, Eisenhardt proposes a system for building theory from case study research by using a rich platform of literature to adopt an iterative stance towards the empirical data and whichever frameworks might represent that data the best. Much like semi-structured interview methods discussed previously, this is essentially a middle-of-the-road, hybrid method of qualitative research which seeks to strike a balance between the relative entropy of a purely grounded theory methodology (although some might argue that Eisenhardt's (1989) proposed system is not

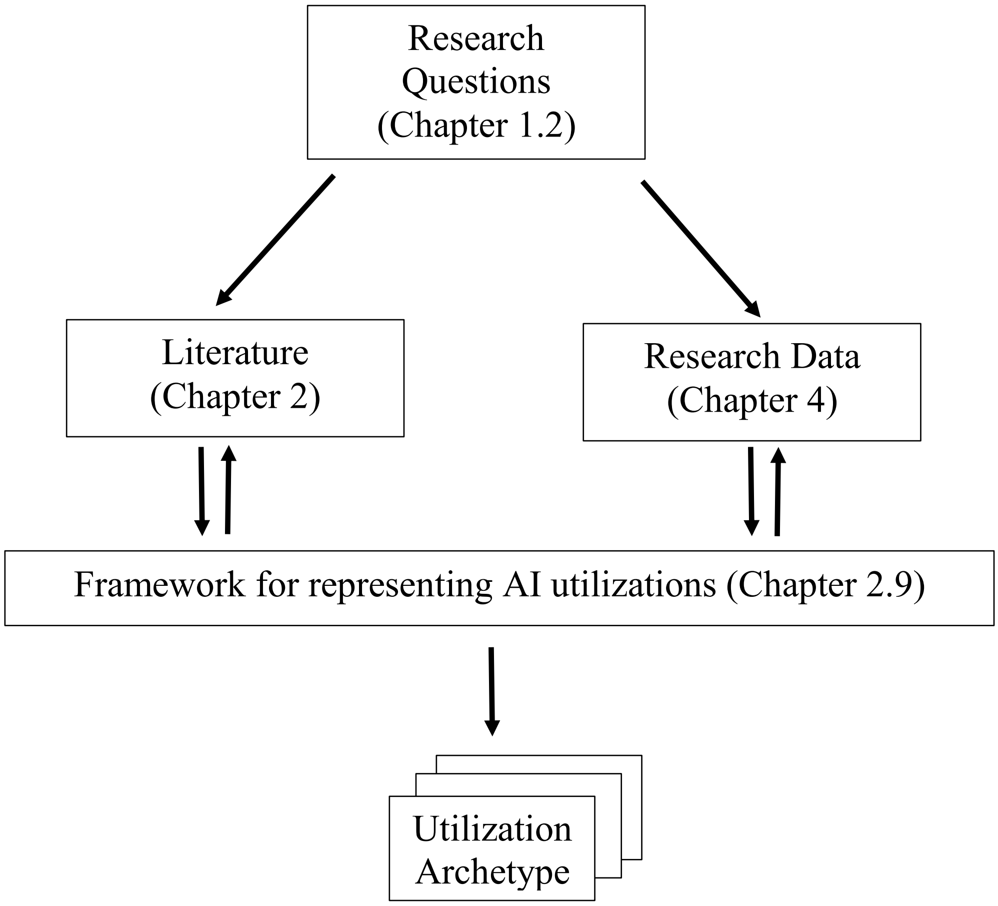

***Figure 5**: Research Design*

that far from something like this) and the more tightly-defined, hypothesis-driven methodology of testing whether empiria fits a proposed theory or not.

The reasoning for selecting a method which allows the data set to participate in the forming of the theoretical framework that represents it was two-fold. On one hand I wanted to ensure that the data would have a chance to express itself in the most natural way possible but still be tied into an established scholarly conversation, in this case about business models and technology exploitation in companies. Striking this balance was important, as the data, and by extension the entire study, would suffer severely if it had to fit into a presupposed framework or a model, or if not fitting into one meant that it was devoid of value. On the other hand, as Eisenhardt (1989, p. 548) mentions herself, her methodology is especially suitable for “[…] early stages of research on a topic or to provide freshness in perspective to an already researched topic”. As AI utilization is a fairly novel topic of discussion, even though it could be generalized as “novel technology utilization” (though one might argue that it would still retain its novelty), a methodological lens that provided the data with a strong, confident voice was chosen.

What this means in practical terms is that a domain of literature and more specifically, interesting parts of that domain and certain constructs were indeed specified *a priori* to the data collection, but the framework only came together after the data was transcribed and had gone through a first pass of analysis, allowing the researcher to establish a dialogue between the data and the literature by using the framework as a translation lens in between. The framework specified for representing the individual manifestations of AI utilization that was introduced in chapter 2.9 is something that chronologically speaking emerged well after the transcription process for the interview recordings had begun, illustrating exactly what Eisenhardt (1989, p. 544) means when she notes that “An essential feature of theory building is comparison of the emergent concepts, theory, or hypotheses with the extant literature”. She also emphasizes the broad nature of the literature base that is needed to achieve this. The dialogue between the literature and the data was facilitated by this framework, which acted as a platform for the figurative discussion. New insights from both the data and the literature would be gathered here and this way the dialogue could be “recorded” or captured in the framework. This idea is illustrated in figure 5. This kind of a dialogue between the literature and data ensures that the final result, whatever it may be, represents the world in perhaps what is a more naturalistic and honest state. A similar viewpoint is echoed by Saaranen-Kauppinen and Puusniekka (2006) who note that it is erroneous to assume that something simply “emerges” from the data, rather that the data won’t speak unless it is spoken to and unless a dialogue is established by seeking viewpoints to the research question through the data. This is exactly my aim with the methodology of building theory from data in a dialogic fashion with the literature, rather than stuffing the data into a framework it only barely fits to.

3.1.2 Sampling

As the topic, in this case AI, is fairly technically complex and as such somewhat exclusive in the nature of the knowledge involved, it was important to find informants who have actual knowledge and experience of the topic. As such, purposive sampling was used to identify companies who would in a sufficiently highly likelihood have experience of the topic. Purposive sampling, according to Etikam, Musa and Alkassim (2016), is a nonprobability sampling method where the researcher chooses deliberately the informants of the study on the basis of the qualities they possess. The exact branch of purposive sampling that this study represents is called Expert Sampling according to Etikam, Musa and Alkassim (2016). According to them, expert sampling calls for experts in a particular field to be the subjects of purposive sampling and it is a positive tool to use when investigating new areas of research or finding out whether a topic should be studied further. The expert sampling was achieved by using the researcher's own networks to determine which professional services companies (see chapter 3.2 for details) have recently publicly stated AI as a strategic path for growth and have spoken publicly about it in their marketing, blogs, at events etc. In addition, purposive expert sampling was used to derive the two companies labeled as "AI end users" (see chapter 3.2 for details). These companies were selected on the basis of the nature of their business and more specifically, the amount of data that business produces which they can exploit in their AI solutions. While it was not certain that the companies would necessarily have employees working on AI or AI utilized in their business, this was an assumption that was made on the basis of their size and in turn the R&D budget of the companies and the amount of data that they produce as a core part of their business.

After identifying the companies, a contact person was established at each company. This contact person was identified as someone who was a manager-level employee of a unit that dealt with AI. Due to the high amount of diversity in the companies interviewed, this meant different things with different companies (see chapter 3.2 for details). This contact person was contacted and met with and the thesis subject was introduced. At this stage it was asked whether the contact person and the company would be willing to participate as informants to the thesis. If the answer was positive (as it was in each case), the contact person was asked to identify 2-4 additional persons in the company that could provide valuable information to the thesis. The criteria for these employees was that they had experience of working with projects that concerned AI and that their titles and seniority levels were still as diverse as possible in order to get a wide enough understanding from each organization about the topic. After this, the interviews were scheduled with the employees provided by the contact person and the contact person themselves.

3.1.3 "Construct validity" of the research

While construct validity is a concept that originates from the research tradition of quantitative research, there have been some calls for qualitative researchers and research methods to spare a thought for the question of construct validity, or more generally the question of "does this piece of research study the target it is claiming to study". It appears that there have been many attempts at trying to define what construct validity would mean in the context of qualitative research as well: Golafshani (2003, p. 604) for instance conceptualizes reliability and validity as "trustworthiness, rigor and quality". The reason for bringing up this concept is the relative ephemerality and lack of agreed upon definitions of "artificial intelligence" in the AI discourse, as discussed in chapters 2.1 and 2.2. This was a challenge from the perspective of the interviews conducted with the companies, as most of the questions asked during the interviews were anchored in whichever definition of AI the informant was using to answer to question. This meant that it was crucial to establish a common understanding of the terminology. However, for the study itself it was equally important to get a true sense of how the informants themselves saw the emerging AI field and how they interpreted it themselves. This was, after all, one of the original motivations of the study and a key research position. The method used to ensure a "construct validity" (or in this case perhaps trustworthiness of the study through shared understanding of technical terminology) was to have the informants define "artificial intelligence" as a concept themselves (see chapter 3.1.4) and to include this as a central data point. This way, it was clear what each individual informant meant by AI regardless of their background, which as earlier established, was varied and multi-disciplinary.

3.1.4 Interview question set

The interview questions for the interviews was initially derived by examining the research question and each subquestion and formulating rough topic areas around each of these. After this was completed, the literature was revisited with these topic areas to see what sort of questions should be created if and when the goal was to find out not only the archetypical utilization models for AI but also the reasoning for the business decisions behind them. Each of these questions was tied to a piece of relevant literature, not counting a few introductory questions that were very general in nature. This guaranteed an explicit connection between the theoretical foundation of the study and the empirical data set, giving each question a theoretical backbone that connected it to the literature review and, ultimately, the research question of this study themselves. As the interviews were semi-structured theme interviews, as noted earlier, the questions presented in the interviews included questions that are not listed here, simply because they were questions that arose from the conversation or were probing questions that related to particular topic areas.

Question	Purpose	Reference
What do you do in this company?	Understanding the informant's position in the company.	A general introductory question.
What is the role of new technology in your job?	Understanding the attitude and relationship the informant has with new technology.	A general introductory question.
There are a lot of definitions and understandings of AI. How do you see it yourself?	Establishing a common understanding of "AI". (See chapter 3.1.3 for details).	Golafshani (2003).
What do you think about the current state of AI and the desires attached to it?	Seeing what the cognitive lens of the informant is related to AI and what their opinion is of the cognitive lens of others.	Kaplan and Tripsas (2008).
What are the challenges that are related to AI from the point of your position as a vendor?*	Gauging the position of the vendor in relation to the novel technology that is examined.	Himberg, Sinkkonen and Särelä (2017).
How do you see the sentiment around AI right now?	Getting a better picture of what the sentiment is around AI according to the informant.	Kaplan and Tripsas (2008)
What type of business challenges your clients hope to solve with AI-powered solutions?*	Understanding the practical business challenges that AI is seen as useful towards solving.	Orlikowski and Gash (1994).

How do AI projects, in your experience, generally generate value to the business [of the client]?*	Inquiring what is the understanding of value creation capabilities of AI from the viewpoint of the vendors.	Chesbrough (2007).
What is the motivation behind projects that utilize AI technologies?	Understanding the motivation of the company to engage in a novel technology, whether it comes from a place of incremental innovation, radical innovation or somewhere completely different.	Utterback (1974).
In what way do AI projects generate end business value?*	Understanding the practical value creation mechanisms of AI projects in order to build archetypes of value creation.	Chesbrough and Rosenbloom (2002).
What kind of competences in your opinion are required for AI projects?	Understanding what kind of competences are required for AI projects and, by estension, for the archetypes.	Danneels (2002).
How would you say that you have seen AI technology and projects develop during the last 5 years?	Understanding the historical context of the archetypes and giving the informant the chance to reflect on the progress.	Abernathy and Utterback (1978).
In what direction would you like AI utilizations to develop in the next 5 years?	This question serves to futureproof the archetypes to at least some extent by understanding the pipeline of AI products and designs.	Abernathy and Utterback (1978).
Do you feel like AI is going towards a "dominant design" or	Understanding whether it seems that there is a dominant design for AI utilizations or that it's	Abernathy and Utterback (1978).

fragmenting?*	actually moving away from that.	
Do you feel like there are different “styles” or “genres” of AI that are taking shape?	This question more directly asks the informant’s position on different archetypes of AI utilization.	Bocken et al. (2013).
What industries or businesses in your opinion would be especially ripe for AI utilization?*	Understanding the informant’s opinion of what a particularly effective AI utilization might look like.	Christensen and Bower (1996).
Is there something you feel like AI is especially good at?	Gauging the informant’s views on what are especially suitable utilizations for AI.	Russell and Norvig (2009).
Is there something you feel like AI is especially bad at?	Gauging the informant’s views on what are especially unsuitable utilizations for AI.	Russell and Norvig (2009).
How do AI projects bring utility for this company?**	Understanding the practical mechanisms of value creation in the focal company.	Teece (2010)
What is the motivation/end goal behind the AI projects?**	Understanding what the reasoning for starting and investing in AI projects in the company has been.	Christensen and Bower (1996).
What business challenges do you hope to address with AI projects?**	Getting an idea about the strategic reasoning as related to the company business model that the AI projects have.	Teece (2010).
In what way do the AI projects	Understanding the practical value	Chesbrough (2007).

create value to the business?**	creation mechanism behind the AI projects.	
Has AI as a technology forced you to re-examine the fundamentals of your business?**	To gauge whether AI has been understood as a radical, company-shifting technology or something that can be fit into existing frameworks.	Tongur and Engwall (2014).
What has been the most challenging part in combining AI with your existing business?**	Understanding the challenges that have risen from AI projects and how those have affected the projects and the cognitive lens of the actors.	Danneels (2002).
What is the best application for AI that you have seen, heard or read about?	To understand the cognitive framing that the individual (and to a certain degree the company) has about AI through their interpretation of "best application".	Kaplan and Tsipras (2008).

***Table 1**: Interview Question Set*

*) denotes questions that were asked exclusively from AI vendors. These questions often discussed dynamics of a client-vendor relationship and how vendors saw their clients' business and as such were not applicable for the end users of AI technologies.

**) denotes questions that were asked exclusively from AI end users. These questions often pertained to the specifics of the business of the focal firm and the personal feelings that the informant had towards AI technologies and applications. While some of these questions might have also been applicable for the AI vendors, they were deemed of higher informational value if asked from the AI end users.

3.2 Data

For the study a set of employees from four companies were interviewed. These companies were divided into two categories “AI vendors” and “AI end users”, as detailed below. The employees in these organizations who were interviewed came from diverse backgrounds, with employees from technical positions such as data scientists, from business positions and some employees from positions of upper management. This guaranteed a diverse set of opinions and views as far as the data itself goes as different disciplines may have very homogenous views within them. A total of 12 informants were interviewed in semi-structured interviews which lasted from 45 to 75 minutes.

3.2.1 AI vendors as a source of information

Two of these companies were identified as “AI vendors”, professional services companies or consulting companies that are in, loosely described, the business of making AI solutions happen for their clients. This could mean any number of things and this is on purpose: as this thesis deals with, at the time of writing, a highly emergent field, it is only natural that it is highly interdisciplinary and rich in its nature, meaning that there are many different business disciplines involved in the production of AI solutions. These include design consultancies, technology consultancies, data scientists, software engineers, business designers, strategy consultants and others.

Company A is a small-to-medium sized consulting company that focuses on strategic design, service design and understanding new technology in a holistic manner and clarifying its transformative capabilities to clients and their business. The company pitches itself as a “Product design and transformation agency”, with a track record of consulting clients about digital transformation and new technology. Company A employs 30-40 people and is located in Helsinki, Finland with additional offices in the Netherlands. Three persons were interviewed from company A: The creative director and one of the partners of the company, the head of strategy and the service design lead.

Company B is a medium-sized technology consultancy that is more focused on software engineering and development than Company A, but still has a sizable design staff and is interested in strategic design in addition to only technology. Whereas company A is a specialized actor that focuses mostly in matters of strategic design and pure consultancy, company B is an end-to-end solution provider that has its roots in software and technology consulting. Company B employs around 400-500 people and is based in Helsinki, Finland with offices in Germany, United Kingdom, Norway and Sweden. Four persons were interviewed from company B: The data science sales lead, a senior data scientist, a data scientist and a senior business designer.

3.2.2 AI end users as a source of information

Two of the other companies were identified as “AI end users”. This essentially means that they use AI solutions for their end business goals, whatever they may be. They differ from the AI vendors by being the party that the AI vendors typically sell products to. AI end users tend to be fairly large companies because of the fact that the amount of data required to successfully build AI applications is just tremendously large, prohibiting smaller players to even begin their building processes. They also need to have access to sufficient computing power and programming expertise, making size yet again a significant factor. It should be noted that AI end users do not necessarily rely on contractors to supply them with AI solutions: both of the companies interviewed for this thesis, for instance, had sizable AI and/or data science divisions of their own. While both expressed that contractors are still used, it seemed that the role of contractors was a more collaborative one than strictly just a vendor. Nevertheless, the end users have a markedly different relationship with the solution that is being developed because it is business critical for their operations. This may make them more conservative but on the other hand more serious about AI as well.

Company C is a large retail company that focuses on groceries. It operates over 800 grocery stores in Finland and estimates that it has around 1.2 million daily customers. It is a company of significant size, with an employee count of around 6700. While Company C also operates a number of hardware stores and a few car dealerships, it is known for its grocery stores and supermarkets, which heavily employ customer loyalty programs and cards. This is partly the reason why it was chosen for this study: A hypothesis was made that Company C must have significant AI capabilities either ready or in the pipeline if it has such a large amount of data at its disposal. This was later proven to be correct by the informants. Three people were interviewed from Company C: a director of online services development, head of analytics and chief data analyst.

Company D is one of the biggest finance groups in Finland, with 1.8 million customers. It offers daily banking services, insurance services and wealth management, along with smaller interests in other areas as well. It operates 170 physical bank branches with around

12 000 employees on the group level all in all. The reasoning for including Company D was quite similar as the reasoning for Company C: While the finance sector operates under fairly heavy regulation from both the state and on the EU level, it still possesses an enormous amount of data that it can leverage to create powerful AI systems. Furthermore, as banks go increasingly digital, so do their clients, interacting with them online and their mobile devices. This makes it possible to develop a quite wide array of services. Lastly, it should be noted, that Company D has publicly expressed a strong interest in AI and is quite active in the Finnish AI discourse. This was also a reason for choosing it as one of the four companies to be examined. The staff that was interviewed from Company D were the head of AI and a development manager.

3.2.3 Analysis and coding of the interview data

Every interview conducted for the study was transcribed in its entire length for ease of analysis and deeper possibilities of understanding the context of what the informants wanted to express. The transcribed interview data was first coded in accordance to the research subquestions of the study along with a section for sentiments about AI and its use. Within these subquestions, the data was further grouped into natural topics that rose and saturated throughout the interviews. In this way, the different topics that were related to the subquestions were discovered and identified. Additionally, it was noted that what was the point of interest of any given quote which was coded. This enabled further perspective for every quote that was selected from the transcriptions.

Based on the coded interview data and the topics that were identified as being saturated, the main research question was answered by building three distinct archetypes that covered all the topics that were identified as significant enough during the analysis. The methodological details for how these archetypes were built can be found in section 4.5 of chapter 4, where the archetypes are introduced and discussed at length.

3.3 Trustworthiness of the study

In this chapter the methods used in the creation of this study have been discussed at length and transparently and as such the reader has been provided with appropriate means to assess the trustworthiness of it. When it comes trustworthiness of qualitative studies, Guba (1981) outlines four aspects along which to examine trustworthiness on when it comes to naturalistic inquiry, a paradigm of thinking that this study can comfortably be labeled as: 1) Credibility, 2) Transferability, 3) Dependability and 4) Confirmability. This study has been conducted in accordance of these principles, taking into account the obvious caveats that rise from the nature of the subject and the experience of the author. The credibility of the study was ensured by engaging in persistent observation at the sites of study and by engaging in continuous peer debriefing with the supervisor of the study and others working on similar studies. Transferability of the study was completed by pursuing a purposive sampling strategy that was not intended to be representative of the group but rather to maximize the information available. Dependability was established by creating a transparent audit trail for the study, which theoretically anyone could use to move from the results of the study to the original quote of the informant. Confirmability on the other hand was ensured by practicing extensive reflexivity throughout the study and by laying bare the intentions and the motivations behind the study. The study can be deemed trustworthy in the context of other qualitative studies of similar epistemological backbones.

4 Findings

In this chapter the empirical data and the findings that were gathered from it will be discussed in detail. In section 4.1, some of the general sentiments that were shared about AI, its progress and the near-term projections of the technology in business use are examined. A significant part of this conversation was also on the definitions of AI, how it was formally defined and on the other hand how the informants defined it to themselves and their stakeholders. Sections 4.2, 4.3 and 4.4 focus on the findings related to the research subquestions that were presented in chapter 1. Each of these sections contains the topics that saturated during the discussions with the informants related to each individual subquestion. In section 4.5 the archetypes of AI utilization are presented and examined. The model that is used to present these archetypes can be found in section 2.9, in chapter 2. These archetypes form the main research output of this thesis and answer both the title and the main research question. They are general enough to be applied to wide range of industries and businesses but specific enough to provide a sufficient amount of managerial value, having been formed on the basis of the entire empirical data set examined in this chapter.

4.1 General sentiments on AI and the discourse around AI

As was expected to a certain degree, the sentiments towards AI as a novel business technology situated themselves on a fairly wide spectrum. Some informants seemed to be especially optimistic and had great hopes for the novel technology to produce added value and some felt it was perhaps experiencing too sharp of an uptick in its hype curve, fearing that it might lead to disappointments, reduced investments or other undesired effects. It should be noted that as all of the informants that were interviewed worked with AI and to a certain degree, excluding a few cases, their career progression was somewhat dependent on the progress of AI as a group of technologies, even the most critical views were more optimistic than some of the public discourse. Another notion to consider would be the fact that it seems that most informants were quite keen to talk about the discourse around AI rather than the technology itself necessarily. This is to a certain degree understandable as the questions also exhibited interest in not only the technology but the discourse, but at the same time it seems that the discourse itself is an important part of the technology, at least in this early a stage in the road to maturity. The discourse itself, as discussed in chapter 2.3, plays also a critical part in funding, research and the very trajectory itself of the technology, so it is only natural that a certain amount of metadiscussion about AI was to be had.

4.1.1 Definitions

As previously stated in the beginning of chapter 2, a critical part of the AI discourse is defining what is AI in the first place, as the actual textbook definition of it is quite open for interpretation (see sections 2.1 and 2.3). Several discussions and comments with the informants focused on this theme, the issue of defining AI for themselves and their customers and/or stakeholders in the company. The topic of definitions is important as they constitute an important part of the technological framing of the actors, as discussed in section 2.5. They are also especially important for AI, because a definition is truly the singular thing that materializes AI as a concept, as it is extremely ephemeral in its nature unlike something like the e-mail, a telephone or an online store. A central theme in this section is the fact that the term "AI" itself is so loaded thanks to decades-long featuring in popular culture before its emergence as a business technology that many informants preferred to shun the term completely and talk with more practical, specific terminology.

> If people are talking about different things you can't really collaborate. So, the definitions that I usually have to give out is that AI is this kind of very general, top level term for computer system that displays human-like behavior, typically in one task or a small set of multiple tasks. But I always say in those talks and presentations and workshops that I don't think AI is a particularly useful term for anyone to talk about because it has so much baggage. You hear AI and people think about like Skynet and that the Terminator is coming to kill them. Because of that and also because there are so many definitions and people use it to mean so many different things it's just very hard to have a conversation about AI. That leads to terrible reporting on the subject, like "Facebook's AI went rogue and developed its own language!" No, they just forgot to put a term in their cost function. It's so hard to engage in a subject where you don't have a strong definition of what you want to talk about, so for that reason I want to avoid talking about AI. Typically, what we do in projects where we sell AI is we build machine learning. Like, there are other rule-based solutions that are used in chatbots and so forth but typically the useful part of AI is machine learning. And there I go for the standard definition, which is probably like "Algorithms that learn from example."
> - *Senior Data Scientist, Company B*

The informant explicitly states that it is difficult to discuss with people about AI due to the usual connotations of "the Terminator" and "Skynet". This led to them avoiding talking about AI, but rather talk about machine learning, and to use the firm definition of "Algorithms that learn from example". The notion that collaboration is difficult if the terminology is not brought down from the highest level is also quite notable in and of itself: It is tempting to use top-level terminology simply because it is easier to say things that apply to at least some part of the top-level term. When more specific terminology is used, it on one hand democratizes the discussion so that it is easier to understand what is referred to but it also sets a certain bar of expertise. Talking knowledgeably about machine learning is already more difficult than talking knowledgeably about something as generic as “AI”.

> Yeah, there aren't really super-specific definitions of AI… I rarely talk about AI because it's such a generic word that doesn't really mean much. I don't even remember when I've last used the word "AI" when I have talked about something that's really relevant. I talk about either data science or machine learning.
> - *Data Scientist, Company B*

Another comment by the colleague of the first informant expresses more or less the same exact opinion. “AI” is deemed too vague and generic to provide value to the conversation, so much more technical lexicon like “data science” or, yet again, “machine learning” is rather used in its place. Vagueness of “AI” as a word is not its only problem either:

> This is a good conversation to have because we try to avoid using the words "artificial intelligence" or "AI" because, at least in principle, it tends to imply that we're trying to model a human's thinking, which is not very interesting or there aren't really reasons to try to model that.
> - *Development Manager, Company D*

“Artificial Intelligence” as a word does indeed imply that there is a certain baseline that is attempted to imitate artificially, in this case the intelligence of a human being or the collective intelligence of humans as a culture. Company D’s Development Manager offers an interesting challenge to this ideal, noting that imitating something that already exists and is widely accessible is not very interesting to his company in the first place. AI solutions, he implies, are something that add something else to the mix which previously was not there.

> I define it to myself so that AI is something that cannot be achieved with if-statements. In other words, something that can't be done with logical inference, but rather something that needs a mass of data and its prediction or assumption of what will happen as based on that data. [...] How clients often see it is that "We have this chatbot, it has AI". Because there's so much hype in AI, it's usually not well understood what the actual role of AI is in a chatbot. In other words, you can absolutely build a chatbot with if-statements and script it very nicely, but in order for it to be artificially intelligent or intelligent, it should be able to understand the logical meanings of sentences, in that if you write it something it should be able to define it and search for semantic meanings in sentences.
> - *Service Design Lead, Company A*

An interesting endpoint to the discussion of definitions and labels is this comment from the Service Design Lead of Company A. They point out that it's not even always clear to stakeholders who buy and use AI solutions what the AI part of the solution is and points out that many things that are deemed "AI" can be actually built with a very long list of if-statements.

> Well I define AI pretty loosely. In my own work, I've always thought that when an algorithm is capable of learning independently concepts from data without explicitly defining them to it, then we're talking about machine learning. AI as a whole is larger than machine learning, the way I think about it is that AI utilizes the methods of machine learning but it also includes how the service looks and feels to the user.
> - *Chief Data Analyst, Company C*

An interesting counterpoint to the question of perceived and "real" AI is the one from the Chief Data Analyst of Company C. They seem to have a quite lax taxonomy of the particular words and note that AI can be in fact a useful nomenclature when referring to a service as a whole and discussing the look and feel of a system that utilizes machine learning technology. This definition in some sense embraces the vagueness of AI as a word and on the other hand understands the importance of user interface design in an interesting manner.

In a somewhat ironic conclusion from the point of this master's thesis, the informants by and large expressed the relative uselessness of the word "AI" itself. It was deemed too vague and open for interpretation for useful work, and on the other hand it was noted that it was quite loaded in the first place. This quality derived from the fact that AI as a concept drew vivid images of some of the negative portrayals of AI systems from popular culture and thus inhibited meaningful discussion about the subject itself, a relatively benign way of learning patterns and causalities from large data sets and applying those learnings to new, ongoing data sets.

4.1.2 Critical sentiments

> There's a hell of a lot of hype in it right now. A colleague of mine just said that when people talk about AI, they generally talk about things that are just massive if-statements.
> - *Creative Director, Company A*

Many sentiments exhibited about the technology and the discourse around it were critical in their nature. It should be emphasized that they were most certainly not negative, or even pessimistic in many cases, but simply critical. This can be due to a myriad of reasons. One culprit may be culture. Of all the informants, only one was not Finnish. Anecdotally speaking, in Finland people tend to have a more critical approach to novel technologies and trends, preferring to analyze them thoroughly before buying into the hype. On the other hand, the only non-Finnish informant of the cohort was also quite critical in their approach, so this explanation may not hold water. Other possible reasons may be the fact that the informants wanted to exhibit a certain degree of contrarianism as a response to the high amount of interest in the public and business discourse. The last, and probably the most likely, reason was the fact that the people interviewed for the study were people who work with AI projects every single day and thus also see the failed projects and efforts from figurative front-row seats. This understandably tempers expectations and creates a tension with the reigning positive discourse.

> Well another thing about it is that… The maturity is affected by the massive amount of hype around it as well. The fact that 'AI is intriguing' doesn't mean that AI is a relevant option for another five years, however you want to define AI. Another slowing factor is, especially in Finland with our tiny language zone is the NLP (Natural Language Processing) side of things.
> - *Head of Strategy, Company A*

Here the informant from Company A makes a very clear-cut distinction between the hype of a technology and the actual viability of it. The amount of hype creates a certain amount of pressure for the maturity of a technology but the maturity of a technology is bound by certain technological realities, in this case for instance the quality and the amount of training data available for machine learning algorithms. Here, the informant is referring to the fact that because Finnish language is spoken by only around 5 million people worldwide, it generates a considerably smaller amount of data than a significantly more common language like English, Chinese or Arabic. Furthermore, as AI utilizations are somewhat dependent on cultural norms and behaviors, training of algorithms is simply more difficult due to smaller data emissions of Finland.

> Another thing is of course the small population of Finland, the data that this country can generate… You know, it's similar in terms of size to the data that is generated in Shanghai by a single neighborhood. That already causes limitations. Maybe this is why there's a certain amount of cynicism that while we're doing really cool things, investing into AI and we have really great talent, the question of data is still present, and they are really picking up speed [in China].
> - *Senior Business Designer, Company B*

Price and the amount of investment was also mentioned as perhaps something that hinders development. However, the issue was not price per se but rather the perception of price and the perception of easiness of implementing and designing AI systems.

> Also, that stuff is actually pretty expensive. Like, if you want to build something on top of Watson, we're talking about seriously large IT investments and not just some service thingy.
> - *Head of Strategy, Company A*

Here, the notion of "service thingy" is significant: as companies are used to buying the latest buzzword-laden offerings from consultancies, be it agile, design thinking, co-creation, etc., AI is not quite as easy to buy. It requires significant investments into data, data quality and pure computational power, not to mention the personnel to wield and control these resources. This is of course a part of the theme about inflated expectations in general, the desire to find a low-cost solution to fix all the problems of a business instantly.

> [...] people really are hoping a lot from it, like AI is some sort of a magic bullet that's going to solve all our problems. Like, there's this history of AI summers and AI winters and I don't know if we're gonna reach another one. I think this summer looks very different than previously but that may just mean that the winter is also going to look different, or possibly even worse if people really invest into something. Like, what is the first catastrophic failure that happens. So that's just one worry that people put too much hope or too much faith in it and the reality might leave them cold, and that could be bad for the field.
> - *Senior Data Scientist, Company B*

The worry by the Senior Data Scientist of Company B is very reasonable. If a technology becomes a conduit for all the anxieties, desires and hopes of business managers around the world, it is bound to let them down in one way or another. On the other hand, if investors get too bullish and regulators cave in to the pressure of easing up the regulation, there might also be catastrophic failures with real human consequences, fatal or otherwise. This would also curb the progress of the field significantly. The central challenge is, then, the question of communicating the prematurity of the technology itself to the management and finding the right balance for investments. Additionally, as Christensen (1997) mentioned, the KPIs need to be set accordingly. A novel technology cannot inherit its KPIs directly from something that the organization and the market is intimately familiar with.

> […] I think the general sentiment is that a lot of people are a bit disappointed. Like, 'we were told that this is AI but in fact our conversions have dropped and if we put an actual human being to do the job the conversion is higher', which is of course natural. When the performance is measured through data or KPIs, for instance that how well a customer service unit is performing, that discussion is still ongoing... I don't have enough information about how the experiments have performed but I've heard that apparently a lot of companies have already abandoned their bots.
> - *Service Design Lead, Company A*

Perhaps this is exactly what the Senior Data Scientist from Company B was talking about earlier. According to this informant many companies have abandoned their customer service bots because they could not match or top the conversion rate of human employees. Is the issue with the technology or the KPIs at this point? This, of course, is an age-old question with a wide range of caveats, but it is still relevant to us. It is only natural that human employees have higher rates of conversions because, after all, they are humans and other humans know how to “operate” them. If a novel technology is measured by the standards of old technology, it is bound to not fulfill those standards. Comparing humans to AI systems is very much like comparing apples to oranges. Humans are slow but capable of extremely complex, abstract inference. AI systems are blazingly fast, but they mostly lack the ability to contextualize and infer information. The Senior Data Scientist from Company B expands on this notion as they tell about workshops on AI that they have organized for the non-technical staff at the company:

> The feedback that we always get is that “before doing this workshop I had heard a lot about AI but we didn’t know what the capabilities were…” And what seems to be the most complicated exercise, seems to be kind of reasoning the errors. In most machine learning applications you can abstract it to a level where you can get either false positives or false negatives, and getting people to think what is the single decision that this thing makes… Bascially getting to that level that is not human-like, general intelligence. That you have a self-driving car that also plays chess and also does this and that. Like, getting that understanding that it has to have a single, defined task. This thing does a single thing, it may do it very well but it still does only a single thing.
> - *Senior Data Scientist, Company B*

This is illustrative of the inflated expectations for AI systems by even employees of a consultancy. Understanding the idea that AI generally refers to machine learning systems that can learn a single operation on the basis of previously existing, high-quality data and then perform that same operation on new sets of data is crucial, however there seems to be a lot of learning and teaching in order for people to get to this point. Popular culture may play a role here as well. AI, unlike many novel business technologies that preceded it, is the subject of several movies, TV series and video games. In media like this, AI is portrayed as robots that display human-like behaviour like inference and complex reasoning, rather than computer programs that predict stocks or weather patterns. This may create a surprisingly difficult situation for attempting to rewire our general perception on what AI is and what it looks like.

> I think we're seeing a very typical discussion right now. […] A certain amount of hyping up something a lot is just a feature of the discourse at this point, it might even take off with a skewed trajectory but at least it gets a lot of buzz around it. After this, the hype may die down a bit like in a typical Gartner graph, but at some point a certain established way of doing things can be found. At some point people also realize that half of what was discussed previously was total nonsense, just discussion that was driven by change agents. These are often of course consultants or technology companies that feed off from change or selling technology. Then on the other hand, the receiving parties are often not as literate in the subject. They may downplay the subject or on the other hand be like "WOW!", and often when they downplay something they still think there's something in it, but they're not sure what exactly. And that's a challenge.
> - *Director of Online Services Development, Company C*

The quote above by the informant from Company C also illustrates the difficult balance of power-play between AI vendors and AI end users. A certain amount of selling is required for any product by any company, which in turn creates an asymmetric balance of knowledge:

the seller typically might know more than the buyer but it is in the buyer's interest to hide this from the seller, rather trying to act cool or even downplay the signifigance of that technology until the buyer has managed to negotiate the lowest possible price. Conversely, it is in the seller's interests to hype up the technology as much as possible in order to negotiate as high a price as possible. While this is of course a crude generalization, and perhaps even a caricature, of a typical consulting process, the quote by the Director of Online Services Development from Company C verifies it to a certain degree.

Although this is not a quantitative study, it is prudent to note that the more critical end of the sentiment spectrum indeed resided in companies A and B. These companies were both what were generally categorized as "AI vendors", companies that design, sell and implement AI systems for clients who use them for their respective businesses. This provides them with a very intimate perspective of how AI systems work, in what kind of situations they are appropriate and what are the challenges of selling those solutions. The question of lining up KPIs, motivations, expectations, styles of production and even human chemistry are questions that are as old as consulting business itself, which is to say that the anxieties and the questions presented in this chapter may in fact be fundamental questions of the consulting business itself, rather than necessarily the business of creating and selling AI solutions.

4.1.3 Positive sentiments

While there weren't many outright positive sentiments even within this cohort of industry professionals, they all seemed to share the general sentiment that the field is growing and most likely receiving a steady stream of investment in the coming years. Although the hype around AI and its constitute technologies received plenty of criticism from some of the informants, some found it positive and in fact vital for the growth and sustained development of the field.

> There's definitely an optimism [about AI] in Finland right now, and I definitely think it's a positive that [the prime minister of Finland Juha] Sipilä floated the idea of making Finland the number one country of AI utilization earlier this year, I was all like "Woohoo, this is great for the field" and I think that it has created discussion and activity in the public sector. I've gotten the opportunity of being involved in that work myself as well and I think it is important, but I also do agree that there is a lot of hype going about it right now. At some point the hype will calm down so that we can develop these things, like AI ethics, in a calmer, post-hype environment. I do think it matters who talks about this and I also try to make sure from my own part that there's always some concrete action behind those words, so that it's not just talk. At the same time, I think we're faced with a such a large breakthrough that we need to talk to each other about it as well.
> - *Head of AI, Company D*

The informant notes the inherent value of publicity and activity in the public sphere in regard to promoting and discussing the novel business technology. This viewpoint is an interesting rebuttal of the idea that there is a point where there is too much hype and additional hype only makes things worse. While the informant is not saying simply that all publicity is good publicity, they are noting the value of active public discourse that may birth topics that should be later revisited in calmer, more established circumstances.

> Recently we have been able to create a lot of solutions, it has been really great to see that there has been such a tremendous, huge interest at the moment and it only seems to be growing. On some level I feel that the growth of interest has enabled the fact that we have gotten resources to create practical [AI] solutions.
> - *Chief Data Analyst, Company C*

Company C's Chief Data Analyst puts it succinctly and rather plainly: if the increased investments are due to inflated expectations and hype, so be it. They still help and they still create interest in the organization and concrete, practical cases that exhibit the prowess of the development team. These cases have the potential to convince the leadership of the company for further, continued investments into AI projects and a virtuous circle will be established. In this way, it is indeed not trivial how AI is being talked about and who is doing that talking.

> Tesco was supposed to lose that entire game because they collected from stores and others built big, expensive warehouses. Then later on, when Tesco won the entire game 6-0, it was of course crystal clear all along. The same people who derided Tesco for being stupid and failing were suddenly of the mind that it was obvious that Tesco was going to win and this is how it was supposed to be.
> - *Director of Online Services Development, Company C*

The final quote of the section illustrates the fact that perhaps the exact content of the discourse is indeed trivial: informant from Company C relates the fierce debate about the feasibility of AI use to the discussion around the early days of online commerce in the British grocery industry. On some level it doesn't matter who says what, since hindsight will always be perfect. As before, the more vague the underlying technology, the easier it is to apply this line of thinking. Since AI as a word is so open to interpretation, it is rather easy to claim retroactively having taken then "correct" side of the discourse.

4.2 Business challenges addressed by AI utilizations

4.2.1 Reducing manual labor

When the actual day-to-day business challenges solved by AI utilization was discussed with the informants, a major theme that rose from the answers was that of reducing manual labor. Manual labor, in this context, refers to any kind of repetitive, predictable labor that is not happening for the first time, i.e. some amount of data exists about it. This includes looking up information, doing repetitive tasks in business productivity software and in general performing tasks that do not concern creation of new, unexpected connections between things and concepts. Needless to say, this is of course a rather idealized version of the tasks that would replace the manual, repetitive tasks that many employees perform now and the reality can just as well be mass unemployment. This, however, is a topic for another master's thesis. The discussions around reducing manual labor that were had with the informants more or less all assumed that there would be more meaningful tasks for the humans who had been freed from the repetitive work that could be handled by AI systems.

> Right now, for instance we are working on an offer to a company where 10 people perform a certain task and we're trying to think whether a machine could perform a part of that and these 10 people could perform in situations where the machine can't really help.
> - *Head of Data Science Sales, Company B*

In a rather clear-cut way the informant tells us that they are working on a solution to automate a task that is now done by 10 people in an organization, so those 10 people then could move on to more value-added tasks that are not possible for a machine. This is probably the most typical utilization use case of AI technology that anyone can think of: replacing humans who do a task that is so simple and well-defined that it could be done by a predictive software on the grounds of data from previous repetitions of that task.

> Our vision for this is sort of that we should be building intelligence augmentations rather than artificial intelligence. Rather than building things that replace humans, we are seeing good results when we build things that support humans, like automating the boring parts of their jobs. The project that I'm working on right now, I can't go into specifics but it's a task that is done by humans in the organization but much of it is manual or repetitive work. It's quite complex, it's hard to write down step-by-step rules for it but, you know, machine learning can do pretty well at it, something like 89% accuracy. So people aren't spending time selecting stuff from drop-down menus and doing boring work. We can save them a lot of time and free up these expensive, trained experts to do more value-added work. So that's where I see at least in the short term where there's a lot of value.
> - *Senior Data Scientist, Company B*

A fairly similar comment by the colleague of the previous informant also stresses the idea of graduating highly trained human experts in the organization to do more value-added work. One more interesting notion is how the Senior Data Scientist mentions that the task is something that is hard to write down step-by-step rules for. This is where the capabilities of machine learning really shine, as otherwise it would be easy to just write a program that approximates the task to the nearest general solution and solves that. With tasks that are *somewhat* irregular but in a larger context repetitive, AI is an interesting option.

> The thing about groceries is that you've got milk, you've got bread, you've got yoghurt, you've got butter, you've got cereal, you've got dogfood and you've got toilet paper. The fact is that you're easily talking about 20 or so different products. Not to mention bigger purchases. Assembling this shopping list is tough for even a smart recommendation system, it takes time. This is why people don't really remember to do this and can't be bothered to do [shopping lists], and then they walk to the grocery store and buy all sorts of stuff and forget half of what they were supposed to buy. If the assembling of this grocery list, especially as we don't shop every day, would happen in the background without you noticing and it would be just one button press away, like "I need this stuff now"... That would really bring out the power of online shopping compared to traditional brick-and-mortar stores, even though I'm not really partial to either, because the bottleneck really is creating that shopping list.
> - *Director of Online Services Development, Company C*

This is another version of the same theme. The informant from Company C describes a situation where they would like to see AI being used: the assembling of a grocery shopping list. A grocery shopping list is, as the informant describes, a suitable task for a machine learning application at a large grocery retailer who has gathered plenty of customer data over the years (as Company C has). A grocery list is a list of products to buy from a grocery store that is long and complicated enough to make it a tedious task for a human but not quite repetitive enough that it could just be created once and forgot about for all eternity from that point onwards. This makes it not a task that is very gratifying for humans, as the variation in it is not necessarily due to applying creativity but simply due to different rates of consumption for previously bought goods. The informant is right then in their assumption that this is something where a machine learning based solution would bring a considerable amount of added value both to the customer in form of easiness and to the organization, in form of more persuasive and semi-guaranteed grocery shopping.

> […] making quick, informed decisions that would take too much time from a human being or that there are so many of them to be performed that it just makes sense to automate them.
> - *Data Scientist, Company B*

The grocery list scenario corresponds to the idea of "making quick, informed decisions" presented by the informant in this case, that maybe don't have a very satisfying return on investment, time-wise, for humans but still need to be done for one reason or another.

> There are situations where, if the human has performed certain manual steps, they may be dropped entirely so that the solution that is being developed would replace those steps. These are things like reading text materials, comparing different data and note-taking. There can also be tasks that have been performed for good measure, to be on the safe side. Those won't need to be performed anymore. Additionally, [these systems] may also change the way humans act. These are situations where the consumer has done a certain step in the process in a certain way and after the solution has been implemented the consumer's role may change.
> - *Head of Data Science Sales, Company B*

This comment illustrates in more practical terms both the tasks that might be automated that have, until now, been squarely in the realm of white-collar work done by trained humans (reading documents, data comparison, producing reports) and on the other hand the change that the consumers may face as well in their role, potentially changing how they interact with businesses themselves. As mentioned before, it is unclear from this answer what those employees who previously performed these tasks would move on to do, but it should be mentioned that it was not asked about either.

> That's partly influenced by my research background. I was working on a project where we were trying to generate a tool for website designers. Like when people draw wireframes, it would try to automatically figure out what the wireframe was and propose interface changes and giving suggestions about the layout. That kind of data-driven approach, it's very difficult to solve the problem completely but it can inspire. Rather than the designer having to sketch 10-20 different proposals… machines are good at that kind of stuff.
> - *Senior Data Scientist, Company B*

Yet another example of a task that is not perhaps something that one would obviously think of as an automation-susceptible, repetitive manual task: website design. Looking at it more closely, we find that in fact website design is heavily influenced by the recent trends in website design and User Interface/User Experience design, making it a beneficiary of a large amount of data from past instances of web design. Thus, inferences such as "with these types of menus in these types of locations on the screen this type of landing page composition probably works well" can be made, moving the human (at least in theory) higher in the value chain, to a more deciding role about web design. This is an excellent example of something that is not the first thing that springs to mind when thinking about manual labor, that can be outsourced more or less fully to AI-based systems.

> The primary thing is efficiency, and with that I mean the efficiency that comes with digitalizing different decision processes and efficiency through automation, that's obvious that in this business that is the area where the primary change in the nature of work will take place. This is due to the fact that there are a lot of knowledge-intensive processes here which are done by humans, humans handle and perform them and search for information and then reach conclusions based on that information. This results in decisions on loan applications and insurance claims, so while AI is not the only thing that's critical there still automating processes and bringing more efficiency to them is a clear area of business value.
> - *Head of AI, Company D*

The informant from Company D implies that such knowledge-intensive processes that are done by professionals like loan applications and insurance claim decisions could be automated at least to a degree using AI. This makes sense. A loan application or an insurance claim are both fairly optimal tasks for a robust machine learning algorithm: a plethora of data exists from previous such transactions, both contain questions that need answers but the answers are situated in a vast amount of data, meaning that it is essentially a matter of manual labor to come up with those answers. This naturally does not mean that loan applications would be solely in the hands of intelligent systems. The more probable scenario is likely one where human labor is discarded from the parts of the process where it is inefficient (Finding, comparing and creating data) and moved to those parts where it is crucial and not replaceable by AI (making the final decision, contextualizing the recommendation from the algorithm).

> Consider a case of automating the checking of X-ray images, for instance. Of course, a human expert, a doctor, needs to actually see the image and determine whether there is a tumor or not, but if there are, for example, 200 of these images you could rank them automatically using an algorithm and it would probably take it around 2 seconds to produce a list that essentially says "Hey check these ones first", so you could prioritize the work order that way.
> - *Data Scientist, Company B*

Company B's Data Scientist continues on this very same theme, suggesting a way of automating a part of a profession that is most likely not typically thought of as repetitive manual labor, a doctor. Here, the informant describes a situation where a doctor needs to look at a mass of X-ray images of patients who may or may not have tumors. It is very possible that some of these alleged tumors may be time-sensitive in their nature and it would imperative to be able to provide care for the patients as soon as possible. However, the doctor cannot know which ones contain image data that at least statistically speaking corresponds with past tumor data. A machine learning algorithm can easily rank the images into an order, which the doctor uses to check the images with the highest probability of containing a tumor first and then progresses down this ranking. This is an illustrative case of a human focusing on the part of a task that benefits more from the unique capabilities of a human, that is judgment based on experience and understanding of the world and its concepts.

> I see it more as something that will provide you with more robust analytics and with that you can reduce your manual labor as well. […] If you think about a scenario where you're trying to understand a market, where it's going and also trying to understand its history, what it is now and the future of it. The same with the customer base: what it has been, what it is now and what it is in the future. Same with the competition. [...] The machine can plot patterns and anomalies and outliers and so forth and then the human doesn't have to do that task. I think work may even become more interesting. That's the dream, at least. Then I could just yell to the machine "Hey is there anything to this idea" and it would just ask me a few extra questions about the geography, the industry etc.
> - *Senior Business Designer, Company B*

The many quotes about automating information retrieval and basic logical inference based on past data seem to reach a saturation point with this quote from the Senior Business Designer at Company B, and it's thus safe to say that this is a major area of AI utilization, as far as specific business challenges go: how to raise the amount of added value of highly trained experts, whose jobs still necessitate a certain amount of elements that one might consider sharing the traits of what is typically thought as manual labor. This group of professionals consists of professions such as management consultants, graphic designers, loan and insurance specialists and other professions that include a significant amount of human judgement and contextualization abilities but also feature a non-insignificant amount of information retrieval, research and analysis of past developments of the field.

> Well it's somewhat double-sided since, at least in principle, if we can make certain processes more efficient we can then reduce the amount of time the consumer's or the company's processes take and that way make it quicker to get a loan decision or any kind of similar service from a bank for that matter. This then benefits both parties in the equation.
> - *Development Manager, Company D*

Finally, the Development Manager of Company D reminds us that while automating white-collar knowledge work may seem like a ruthless search for maximum financial efficiency, it is not quite so black and white either. If certain services that are known to take time or are time-critical (a loan decision for a mortgage fits both of these descriptions) can be offered to consumers at an optimized rate, this raises the perceived quality of the service and would most likely result in positive perception of the product and/or the company.

4.2.2 Getting rid of human bias

A number of informants were also hopeful about the possibility of eliminating human bias from business and thus accelerating more economically sound and perhaps even more ethical, unseen business decisions. The theory is that if a machine learning algorithm or an "AI" can reach a decision that is based on purely data, this decision would be free of biases against race, sex, social and economic class and other factors that can potentially cloud human judgement when it comes to other human beings. In principle this is true, although it hinges on a few key conditions. Firstly, the data itself most be not be skewed. If an algorithm is to be trained to be unbiased, the data it is trained on needs to be unbiased as well. As the data usually is based on human action (or inaction), this can present a significant challenge for an organization that is interested in getting rid of biased decision making via AI systems.

> Actually one of the things they were interested in was predicting failures and we were like "Okay, how many failures can you show us?" and they were like "Not that many…" They sent us this dataset that had like three million rows in it and of those three million maybe a couple of thousand corresponded to failures, and we were like "Okay, that's pretty unbalanced." Also they just didn't have a very firm definition of what failure meant, those few rows were their best guess. So I guess when people develop new products they could figure out what to even log, what does a success and a failure look like.
> - *Senior Data Scientist, Company B*

The quote above is an extremely illustrative example of the challenge of acquiring high-quality, unbiased data. The company in question had failed to log and even define what a failure meant in their situation, which made predicting failures understandably impossible, at least with that particular data set.

Second, the organization needs to be able to actually heed the recommendation given by the now hopefully unbiased algorithm. This poses a tricky situation, since in the previous chapter it was argued quite clearly that the final call on decisions should still be left to humans. However, if humans make the final call, how do algorithms reduce bias? A certain willingness to let go of power is needed from people who work with AI systems as their tools in their day-to-day jobs.

> We are very good at seeing patterns, but they are just not that accurate. Cognitive bias affects our thinking all the time, whether we want it or not. Algorithms are pretty neutral, as long as they are kept neutral. One thing that's interesting about design is that when you incorporate algorithms with it... I think this has been studied at MIT for a few years. For example, when joining pipes together, what is the most lightweight, efficient way of doing it? When this question is put through an algorithm, the answer looks very different than a joint made by a human.
> - *Creative Director, Company A*

The informant notes that even such a routine, relatively value apolitical action as joining two pipes together may have cognitive biases in the form of heuristics and conventions, going back to perhaps the education that the person joining the pipes has received and even the education that their educators have received. An algorithm which has used countless conjoined pipes as its training data will execute the joint in the most efficient, lightweight way possible without having to carry the history of convention in the industry into its actions.

This may sound like an incredibly trivial example, but it can have significant effects as conventions get questioned and bypassed. When the question moves on from the joints of pipes (not that they are not important, as they can represent critical HVAC functions) to human beings, the stakes for getting rid of human bias get even higher.

> Well the prior situation was that a human being would read all these applications and now a machine is reading it. The fact that humans don't read them anymore changes the situation, the machine is more democratic. The system also finds combinations in the applications that a human couldn't find and wouldn't even think of.
> - *Head of Data Science Sales, Company B*

When going through something more sensitive with a high degree of possible bias, like job applications as in the quote from the informant in Company B, getting rid of bias is tremendously valuable not only to the applicant, but also to the company. The AI system can, as mentioned, pick out combinations and traits that would simply elude a human HR professional due to any amount of reasons. In a scenario like this, human beings would still most likely do the final selection of candidates but an AI system with no bias could rank them in an order that a human being perhaps couldn't, simply due to their inherent cultural and environmental biases.

> Well, one example that I remember very vividly was when we were analyzing tools that are related to building a sauna. There, winter ice fishing overalls came up very prominently as a product that was purchased together with those tools. That sounded weird at first, but then again usually when you build a sauna it is or it can be quite cold so a very sturdy set of winter overalls is a perfect piece of equipment for that. But this is really an example of something that a human wouldn't have thought of.
> - *Chief Data Analyst, Company C*

Seeing what comes out of analysis without human bias can also create unique business opportunities. Asked about a situation where an AI system gave a result that a human probably wouldn't have, the Chief Data Analyst of Company C tells an anecdote about the AI system identifying a heavy set of winter overalls meant for ice fishing was actually a useful piece of equipment for building a sauna, although on a surface level it doesn't make any sense at all. This is due to humans having a bias that tells us that ice fishing overalls and tools for building a sauna are in separate categories of product, even though in reality they are used in tandem.

> There's of course better decision making and better decisions typically always save money. I mean that simply by the fact that with better decisions you avoid erroneous investments by allocating your money better. If you have ten different cases to invest in you should allocate the money to the ones that have a higher chance of succeeding, thus minimizing uncertainty. [...] Just in Finland there are many examples where if someone had just said in an early stage that "Hey don't go to the Russian market" they would have saved X number of hundreds of millions.
> - *Senior Business Designer, Company B*

Pride and confidence are also forms of bias in some cases. The informant from Company B notes that reducing human bias in investment decisions could potentially save large sums of money by providing a second opinion through a large amount of data that is analyzed quickly and reliably.

> So it's something that's kind of boring… but the idea of a self-driving car or a self-driving vehicle is kind of revolutionary, because people are terrible at driving. It's one of those areas where we're killing the planet, buying more and more cars and driving them inefficiently causing congestion and people have trouble moving in cities… And self-driving vehicles have amazing potential to solve those problems, or like smartly planned routes have with on-demand vehicles. You may have seen concept images of these buys intersections of cars just passing by each other with millimetres in between because they all just know exactly where the other vehicles are and they can perfectly coordinate. I think that vision of future is very powerful and cool.
> - *Senior Data Scientist, Company B*

Another variation on the theme is the act of driving. Driving can be done efficiently and safely, it just can't be done by efficiently and safely by humans. We tend to like certain routes better than others, we have slower reaction times than machines and we can't control the emissions and the engine of a car the same way an integrated AI solution could. While this example is not entirely about human bias, it is yet another case where removing the human from the overall function would result in a better, more rational approach. As stated earlier in the beginning of this section, this is an approach of utilizing AI that requires significant managerial and psychological changes from the organization itself. When simply reducing manual, repetitive tasks it is easy to still perceive the human as the master of the AI, essentially creating a subordinate-like relationship with it and delegating tasks to it that are clearly lower in the value chain than the ones performed by the human. However, when moving on to utilizing AI as a bias remover, the relationship gets significantly more complicated. Here, the human must essentially succumb to the will of the machine, even though they might disagree with the inference of the AI system. They need to override what is commonly referred to as the "gut feeling" and go with the cold, calculated facts of the AI. Suffice to say, this is much easier said than done.

4.2.3 Solving problems that were previously unfeasible to solve

A small but intriguing subsection of business challenges tackled by AI technologies are challenges that were previously unfeasible to solve due to their scale, expense, difficulty or, as is the case most commonly, some combination of these. These are challenges that have become so conventional and ingrained to the logic of business that in some cases they define entire companies and industries. While this is clearly a utilization category that is in its infancy, judging by the amount of discussion during the interviews, it is something that has perhaps the most disrupting effects out of all three business challenges discussed here. If AI systems can question the very logic of entire industries, it may mean that industries themselves may have to re-define their limits.

> What I'm seeing is right now is the cloud processing stuff, where you speed up certain things like character recognition and manipulating images etc… Essentially you speed up things that have been done before as well. Rather than calculating exactly, you let the AI do the work for you. Then another category could be optimizing extremely large data sets. [...] Like optimizing the cooling algorithms for AC equipment in server halls or winning a match of Go. Those two are things that, in my opinion, are classic AI, very smart stuff. Solving technical problems that have not been feasible to solve previously and generating value through that.
> - *Service Design Lead, Company A*

Winning a match of Go and optimizing the cooling of a server hall in a real-time fashion may seem very far apart from each other but they share something that can go unnoticed easily: both were problems that were previously thought of as unfeasible, and as such not even attempted. Winning Go may not carry much direct business impact but the prize for being able to predict and change cooling of buildings and industrial sites like server halls in real-time has potentially massive upsides, both in terms of environment and the bottom line of the company in the form of a reduced electricity bill.

> I think there's plenty of ground to cover still in term of making processes quicker, to bring the right kind of data and the right kind of enriched or analyzed data to the mix so that we could show the direction your personal finances are going to and also what we have identified from your finances that you should maybe consider about. These are things you'd think you'd go through with a customer when they apply for a mortgage or something, to see what kind of things are happening and how much they are earning and saving but they're really conversations that take place after five years then fifteen years, so it would be beneficial if that could be incorporated into day-to-day operations.
> - *Development Manager, Company D*

The informant from Company D expresses that in the financial institution they work for are business functions related to customer solvency and personal finance that do take place as required, but they are perhaps not an optimal level. The optimal level (daily, essentially), in this case, differs so much from the economically feasible level (every five to fifteen years) that performing these tasks at the optimal level is not feasible and this has been a convention of the industry for years. With AI systems, however, reaching the optimal level becomes a trivial question because the operating costs are so low, after initial investments of course. This has the potential to cause a significant amount of change in the banking industry. Another avenue of this same problem category is the question of recommendations. Recommending things of course is not exactly a novel business technology but doing it accurately and efficiently with little to no input from humans is still a problem very much worth solving.

> One of my favorite examples are the recipe recommendations that can be found in our mobile app. There we have been able to combine web data with the historical purchase data from individual customers and through that we have designed a model that can predict, based on the customer's purchases, what kind of recipes they most likely prefer. We have 7000 recipes, which is great since there's definitely something for everyone there, but then again that 7000 recipes is a lot of recipes for a human being to go through. So, if we can, for instance, provide the customer with 100 recipes ranked in an order of suitability, that pretty much solves the problem for finding recipes.
> - *Chief Data Analyst, Company C*

Recommending and finding items, recipes and other content from large databases with supreme accuracy and predictive capabilities is now something that can be done with relative ease. This may change the way that, for instance, complicated, highly customized products such as cars and industrial machines are sold as it enables the seller to pre-assemble and offer combinations that reach the optimal level of profitability for them and desirability for the customer, thus maximizing profits (or any other given KPI, for that matter).

> I guess it's interesting because every business has content of some kind, whether it's the products that they sell or ads of some kind that are served to you, or articles or videos that they have. Everyone has content, so personalization is an incredibly general thing that can apply to almost any industry.
> - *Senior Data Scientist, Company B*

A very powerful notion by the Senior Data Scientist of Company B is the idea that every business has content of some kind that needs to find the most optimal recipient, be it advertising, products, services or media. A fishmonger has content in their business, which of course is the fish, in the same way that a company like General Electrics has content, in the products that they produce. Without a party that is willing to pay a price that satisfies both parties, this content is essentially useless and devoid of value. This is why it matters a great deal that the delivery process of essentially any kind of content can be analyzed and understood through AI systems.

> We created a spam handler for [a mobile gaming company], they received a lot of different spam and trolling that a human being couldn't even delete in the first place. Just a variety of very nasty stuff. We developed an algorithm that can recognize when we're dealing with spam and when we're not and it's working very well. Customers won't even notice it. The customer only notices when it doesn't work, because then the spam gets through.
> - *Head of Data Science Sales, Company B*

Essentially building an extremely high-quality spam filter is an inverse version of a recommendation engine: it identifies content that should not be shown to the user under any circumstances and then hides and/or deletes that content. This is also something that, by using explicit rules for keywords and similar techniques, would result in an endless cat-and-mouse game with the spammers and the people who are attempting to filter the spam, as the informant themselves note as well.

Obviously, these are not the only business challenges that AI systems can tackle. They are but a fraction of all potential uses for the novel and diverse group of technologies, but an interesting and important fraction nonetheless. They represent three different categories, each with a relatively clear-cut theme and an understandable value creation and capture mechanism. For the closing words of this section, we turn to Company A's Creative Director:

> If we're talking about machine learning, I'd say that at its best it fits right into the core [of the business]. It improves the existing service, makes it more accurate and makes it deeper.
> - *Creative Director, Company A*

As they say, we have seen examples of AI use that indeed improve the existing service, make it more accurate and make it deeper by using a combination of data, computing power and creativity. In the next section, the critical competences required from the organization and its employees to create these examples and other utilization cases are discussed.

4.3 Critical competences identified for successful AI utilization

The critical competences required for successful AI utilization were also discussed at length with the informants. While some of the comments were quite predictable, pertaining to the importance of a technically sufficient staff with data science expertise, there was also a surprising consensus about the importance of understanding the business dimensions of the question at hand. Teamwork and communication were also mentioned as crucial factors. This is hardly surprising because, as previously noted, AI is at best a rather vague proposition: it needs to be processed somehow to produce an end product that creates value, much like a raw ingredient or a utility.

4.3.1 Business expertise

Time and time again there was a call for business expertise and understanding of the "business side of things" by the informants. This was not entirely unexpected or unheard of, but still surprising as typically AI and data science are most likely thought of as very technical and IT-heavy processes.

> If the starting point is that the client says "Hey we have some data over here, what should we do?", business expertise is required in order to understand that what are the strategic goals of the client's business, what is the outcome they would like to have and that takes business expertise and, of course, data scientists as well. We often also combine them with a service designer. The service designer designs the service itself in a novel way.
> - *Head of Data Science Sales, Company B*

The informant expresses that clients sometimes do have a rather vague starting point from the perspective of the AI vendor: We have gathered a certain amount of data of certain kind, but we're not quite sure what to do with it. This is not an issue that can be solved by a programmer or a data scientist, at least alone. It calls for someone who understands the strategic forces that shape the client's industry, what is the trajectory of those forces in the near future and what is the role of the client's company in the market. After these questions have been answered, the KPIs and the goals can be plotted and the practical design of the AI system can begin.

> One thing about this is, something that I also faced with analysts for a long time, is that when [data] analysts know what the data is capable of, what data exists and how to crush it. Then they always ask the business side what they want, and I just reply "Well what can you do?", they reply "We can do what you want us to do", then I go "What if I don't know what I..." Everything is possible but nobody knows. [...] The way to end this loop is that you take something that is extremely trivial and just produce a practical application for that.
> - *Director of Online Services Development, Company C*

The Director of Online Services Development for Company C notes that without a certain degree or ability of being able to be proactive and asking the right questions, there is a possibility that the organization ends up in an endless loop when it comes to AI utilization. The technical side of the organization wants to know what the business side wants and the business side wants to know what the technical organization can do. This further underlines the need for leadership and vision when it comes to forming new technology strategy for the company, as an abundance of possibilities can lead to a crippling amount of choice. The informant continues by suggesting that the way out of this loop is to just try something trivial (supposedly so that if the project fails the participant can come out of it with minimal amount of face lost).

> Right now, there are really great machine learning experts in Finland and the tools for that exist and there are people who can create things with the tools. Another area altogether is the business understanding, as in is this model worth doing in the first place, what does the result of this model mean. This is the case now especially when a large portion of people with machine learning expertise don't originate from the finance sector and that means you are facing a significant dialogue in the development between the recipient of the model and the vendor of it. This obviously does not change whether the vendor is an external company or not. You still can't assume that here's the model and it works because there are so many industry-specific forces in the finance industry that can only be understood with expertise.
> - *Development Manager, Company D*

Yet more emphasis on the importance of understanding the reasoning and implications of the AI solutions that are created or are about to be created. In this case the informant stresses the importance of understanding the particular industry and business that is in question and questions the idea that one size of AI application would fit all.

> Well, just listening to the business/client side of things as the first thing is incredibly important in understanding what the problem is that we're trying to solve. […] It needs a bit different skillset than just data scientists. Of course, when you're actually coding the system there needs to be some prototyping, just to see what it's shaping up to be along the way.
> - *Head of Analytics and Customer Data, Company C*

Company C's Head of Analytics and Customer Data refers to a "different skillset than just data scientists" when they are talking about solving the question of understanding what the problem that is being solved is and/or should be, in the first place.

> In order to gain an understanding of the situation, it'd be great if the math genius would have some sort of a Business 101 course under their belt and at the same time the other side, the designer, the developer, the business consultant, they should also have some sort of understanding of the statistics and the math involved.
> - *Senior Business Designer, Company B*

The informant here calls for a bridge of expertise between the team members, each with their core discipline that they are the undisputed experts of with an understanding of other disciplines that is enough to engage in a meaningful dialogue and find common grounds with them. This as a concept is highly similar to the idea of "T-shaped" people, sometimes attributed to Tim Brown of design consultancy IDEO.

> It's important the business side that is going to receive the AI solution has a genuine desire and interest in participating in the development. Then, taking a step further into the development side of things, I think that there needs to be a person between the business side and the actual team that's doing the coding that can speak both languages. We have a scrum-style structure where there is a Product Owner whose role includes that they can talk to the business side so that they understand what's being talked about and at the same time they can communicate that to the coding team in a sufficient manner. They are sort of the link between development and business.
> - *Chief Data Analyst, Company C*

In a very similar comment the informant from Company C wishes for a person who acts as a link between the "vendor" (vendor is in quotations since this can be, and often is, a unit that is located internally within the same company) and the recipient of the AI solution. This person needs to be able to understand the desires, anxieties and motivations of the both parties during the process and be able to communicate between them speaking, as the informant put it, two different languages.

> When you start a project [like this] you certainly need a data scientist to think about what should be done. When that has been found, you need a business person who understands where the value is located in, as in alright, this is pretty easy to solve but it contains no value so we probably shouldn't do it. And that should be the first steps.
> - *Data Scientist, Company B*

As we can tell by the number of the quotes and how they are spread throughout the different companies involved in this study, the necessity of a person with business expertise is crucial and in demand, at least when it comes to developing AI system utilizations that deliver actual value to the organization and its customers. The challenge is of course being able to create this position, as it is an order of magnitude a vaguer one than a Data Scientist or a Software Engineer.

> My job is a diplomatic one… I engage in dialogues and move things forward, which means that I try to understand the needs of business, the needs of development and the challenges of business and I then try to interpret them in such a way that we could through machine learning or other data science either support it or get rid of obstacles or make people's jobs easier.
> - *Development Manager, Company D*

The informant from Company D essentially describes his job to be the very same one as the one described by the informant from Company C previously as an important task in developing succesful AI utilizations. They engage in dialogues between business units that depend on each other for the best possible result but share otherwise little in common. Curiously the informant describes their job as a diplomatic one, perhaps likening themselves to being an ambassador of both disciplines to the other side, whichever that may be depending on the situation. It is clear however with this quote that this role is not only required, but it actually exists and is used by organizations who develop AI based systems and most probably extract business value from them.

4.3.2 Cross-disciplinary collaboration

Some respondents also brought up the importance of engaging other disciplines than the usual suspects of business, technology and design in the process as well. This was most likely due to the nature of AI itself: If developers of algorithms wish that they represent the material world as best as they possibly can, experts from many different fields are required to even begin to approach that level of accuracy in modelling. Another reason for this is the blank slate -like quality of AI as a group of technologies, which was already discussed earlier in section 4.1 and elsewhere in the thesis. As we are dealing with such a malleable technology, it needs people with the expertise of whichever industry it is molded into in order for it to be a right fit. This is essentially a more specialized version of the scenario that was talked about in the previous section.

> You hear startup pitches that don’t hold up to more than 10 seconds of introspective thought. Some startups wanted to hire more people who were like the people who already worked at the company, so they were interviewing employers and building this knowledge space and finding applicants based on that. And I think that building echo chambers as a service is just… Like, anyone who has ever thought about social psychology or the dangers of groupthink can tell you that this is a terrible idea. But Silicon Valley hypercapitalists were just like “yeah, culture!” I hope there’s going to be more ethical thinking and social scientific thinking, I think this is a time when humanities have never been more relevant. You know, you hear about companies hiring philosophers and ethicists, I think that’s a good trend. I don’t know if they are being utilized properly but cross-disciplinarity and having more viewpoints at the table is probably the way to making sure that we don’t accidentally build a dystopia.
> \- *Senior Data Scientist, Company B*

The informant expresses interest in engaging experts in ethical and social scientific thinking into AI system development because of their worry that the relative homogeneity of the technology industry may result in groupthink in the long run and issues such as ethics and questions of human behavior will simply be overlooked. Immediately after saying that they also contemplate whether some of the philosophers and ethicists that have been hired by companies so far really get utilized properly, or more likely, have enough power to change the course of projects. This is certainly a classic problem of cross-disciplinary teamwork that was also briefly explored in chapter 2 as well.

> [...] I talk about the fact that a central challenge is how to get the experts from the banking side of this company, to get the experts from wealth management, doctors, educational scientists and lawyers to understand enough about this technology so that they can start innovating as well.
> - *Head of AI, Company D*

Company D's Head of AI also paints a vision of multidisciplinarity in AI development, hoping that a variety of professions could establish a baseline understanding of the technology so that they could get over the technical hurdle and start thinking about different utilizations of AI systems from their unique perspective of expertise within their own disciplines.

> [...] you need to have the math and you need to have the engineering, but I think that recently increasingly the designer… That's something that in the past we might not have done so much, like the designer might have consulted briefly and the data scientist and the engineer went and built the thing. But now as it becomes clearer and as these public failure cases in machine learning have kind of come out, they're also design failures. Like the Microsoft chatbot that went rogue and started tweeting hateful stuff. That was a design problem. No one thought "hey what's the worst thing that someone could learn from Twitter". Thinking about the errors that can occur and how to recover from those and how to make the right ethical choices and how to find a problem that's really worth solving, those are all design problems. So that's one of the reasons why I started doing those workshops, I feel like we need to collaborate better with design.
> - *Senior Data Scientist, Company B*

Lastly, the Senior Data Scientist of Company B talks about the importance of understanding the nature of the problems that one is dealing with and that although we are dealing with software, algorithms and maximizing profits, the problems themselves may not actually be related to these areas of expertise. A rather well-publicized case of machine learning utilizations that failed was Tay, the Twitter-based chat bot by the software company Microsoft (Vincent, 2016). The failure of this chat bot, according to the informant, was in fact a problem with its inherent design principles, and not with the software. A designer specialized in user-centered design might have noted that if a machine learning algorithm would use Twitter as its data set, it might receive a large amount of hate speech and other unwanted data to its data set. This, however, apparently was not concerned and Tay had to be shut down.

If some issues and topics divided the informants before, this topic area certainly was not one of them. It was deemed with nigh-unanimous certainty that a certain level of business expertise is crucial in order to understand the actual sources of value and the mechanism for their capture, and on the other hand that cross-disciplinary collaboration was necessary if successful AI utilizations were to be built.

4.4 Business model implications of AI

Moving on to business model implications of AI as a group of technologies, it was clear that many informants felt that the gradual spread and diffusion of AI into various industries could spawn entirely new sources of value and mechanisms of value capture for firms. This is less grandiose than it sounds like. Any new technology that is widely adopted will change the dynamics of value capture in some way, but the progress is usually gradual and not very dramatic. In this section, some of the ways that the respondents felt that these changes may materialize themselves will be outlined.

4.4.1 AI as a "booster" technology

> A colleague of mine said this so don't attribute it to me but… They said that asking the question of what does AI do the best is pretty much the same as asking what does the internet do the best.
> - *Head of AI, Company D*

Several informants felt that an apt comparison for AI technologies and their effect on industries would be other monumental technological shifts that disrupted some industries but effectively turbocharged others, leaving the industry structures more or less as they were before the technology. In essence, this is the idea of technology as a booster. A fabric mill is a fabric mill, whether it is powered by steam, electricity or any other source of industrial power: The change is related to scale, not necessarily the core business. Certainly, it can and should be noted that when the scale of a business changes enough, it does affect the structure of the company and its revenue stream as well and it can be argued that this type of change in the production scale is, in fact, a change in the business model itself.

> For us AI is an enabler. It enables more accurate data, better experiences and more seamless experience for the end customer.
> - *Creative Director, Company A*

This is not to say that this role as a booster or, as the informant put it, enabler will become the legacy of AI. It's simply a phase that is a part of its ongoing trajectory from a fairly novel, immature business technology towards something that is at the same time very mainstream and at the same time has quite specialized, nuanced business models that have been built on top of it. A rather natural comparison could be the evolution curve of online shopping. The first online stores operated much like their brick-and-mortar counterparts, except online. The medium was the only change. Comparing that to where companies like Amazon are in 2018, the difference is stark. Free shipping for subscribers, flash sales, affiliate links, and other online-specific value creation and capturing mechanisms are more and more common.

> I think what's happening in this sphere right now is that people are starting to understand that AI technologies are tools and super-boosters for things that have existed for thousands of years. I think the internet is more or less the same as Gutenberg['s printing press]. It's just a digital super-booster, the tool box has grown and efficiency has gone up.
> - *Senior Business Designer, Company B*

This idea of AI as a booster of previous concepts is expressed by the informant from Company B. The note that internet also was a booster for something else, in this case the printing press, which on the other hand was also a booster for hand-set letterpress. AI then should be thought of as same way: If an opportunity to supercharge a company would be offered, what would it look like?

> Human beings are very individual in their nature, but at the same time they are very similar in groups. What gets customers like me to commit may not be that big sale ad on Helsingin Sanomat [Finland's biggest daily newspaper] that gets surprisingly large amount of financial investment. What works for whom, there's a lot we could improve with that understanding. And, I guess it's called mass-customization, that we could learn about every single customer sufficiently. No analyst can personalize two million households. But systems like this certainly could learn to do that.
> - *Director of Online Services Development, Company C*

The fact that no analyst can personalize two million households, but an AI system can is fascinating and, ostensibly, very true. Humans are very good at certain things, like understanding fuzzy connections of concepts and drawing links between abstract subjects using human culture as a medium. However, scalability of a human, an analyst in this case, is notoriously poor. In this example an AI would essentially boost the personalization function of the company to levels that were previously unheard of. It is essentially still the same personalization that existed before but at a massively different scale and accuracy.

> The customer experience, having a 24/7 customer support, that would be the goal. If you have a problem, you could always get assistance for it. But if you establish an actual 24/7 customer service helpdesk, the costs may be so high that it can't justify the investment. If, say, 80% of those issues could be solved through intelligent bots or some sort of AI, that would be a clear business case.
> - *Service Design Lead, Company A*

A very similar example is the one that the informant from Company A is talking about. Customer service is a function of most consumer-facing companies, but 24/7 customer service is available only for a select handful of large corporations who have decided that the cost is worth the improvements in customer experience and brand image. However, AI systems could potentially boost the customer service capabilities of even smaller companies so that 24/7 customer service would be more a rule than an exception. The business model implications of this are as follows: If all companies can boost the rate of their tasks that require repetitive, manual labor to a theoretical maximum, then that is no longer a competitive advantage for any single firm.

> For instance, creating product selections on a store-level, there you basically face the same core issue. Humans can do decent selections, but then again if the task is to do a selection that takes into account 1000 of the best customers of that particular store you can bring in so much information into the task with AI that would just be too much to handle for one or even several humans. It would just take too much time.
> - *Chief Data Analyst, Company C*

One example of this is the idea of having a superior selection of products as the competitive edge for a general goods store, like a grocery store described by the Chief Data Analyst of Company C. If, in theory, all stores can tailor their product selections to an absolute perfection for their customers, the competitive edge needs to be found elsewhere.

4.4.2 Humanity as a competitive asset

Scarcity is a powerful selling point. This is a not merely an opinion, but a fundamental economic truth on which much of modern capitalism has been built. If AI systems start performing more and more consumer-facing tasks that were previously performed by humans, the element of human contact is reduced. However, in certain professions human contact is an integral part of the profession. This does not mean that it cannot be reduced from those as well, but it may mean that human contact can become a unique selling point that is marketable in the same way as any other selling point, like quality or price.

> If you think about automating medical diagnoses, for example, I think that in situations where meeting the customer and having a certain human contact is important, it's not that great of an idea to start automating those. If you go to a doctor's office, that experience is much more than you inputting your symptoms into somewhere and getting a diagnosis and a verdict as an output, it's also about interacting with another human being. They are situations that require emotional intelligence and the ability to establish that human-to-human contact.
> - *Data Scientist, Company B*

An interesting take from an informant who builds AI systems daily in their job. Yet, it is easy to imagine that fully automated medical facilities for non-serious symptoms will spring up at some point, which creates a two-sided market for health care: One with humans and one without them. Will human doctors become a luxury commodity for wealthy patients solely?

> Well, in the long term many things are replaceable by AI. I don't think, however, that human contact and meeting other human beings and understanding them and being able to empathize with them are things that in the near future will be in reality replaced by any kind of AI in the larger scheme of things. And of course, if you look at the creative industries, you can already produce many kinds of art with AI but the way I see it is that that's where human beings will have a major role for a long time in the future as well.
> - *Chief Data Analyst, Company C*

A very similar comment by the informant from a different company suggests a similar manner of thinking. There are certain tasks and concepts, like being able to empathize and provide human contact on which humans have a relative monopoly on at least for the foreseeable future. “Relative” being an imperative word because price is still a very attractive source for leverage when it comes to competition. If AI systems can provide even a fraction of these sources of added value by human beings they may find a market, making human contact essentially a premium commodity.

> The way I see it, the tasks that are left for humans to do are the ones that are expected from humans. Take paintings, for example. If you expect a painting to be painted by a human, then it will be painted by a human, meaning that the consumer behavior of consumers is something that will keep it in the realm of human tasks. If you expect going into a meeting to meet a human there, you will meet one.
> - *Development Manager, Company D*

The informant expresses confidence that the market mechanism will retain humans in the workforce doing tasks where humanity is of added value. Perhaps so. Software-based solutions, however, have essentially zero variable costs, whereas humans have linear, and in most cases growing variable costs. The temptation of fully automating everything that can be automated is, from a strictly financial standpoint, quite understandable.

The effects of this idea of “human premium” on the business models of companies are significant. Firms will have to answer the question of whether they see humanity as a value driver in their business, something that raises the perceived level of service and exclusivity for their customers or is it an extra cost that should be cut, preferably sooner than later. Surprising combinations may spring up as AI systems become more commonplace, with unexpected industries finding value in human contact, with unexpected premium segments in industries where such division perhaps did not previously exist.

4.5 Archetypes of AI utilization

How should the different use cases heard throughout the interviews be roughly classified then? Classification, obviously, is to a degree an arbitrary exercise where much is left to the discretion of the classifier, this is something that is absolutely recognized in the context of this thesis.

> Before I worked for [Company D] I was a consultant and back then we used to often start from the assumption that you have a certain set of use cases and then you use them and as long as you have done the same use cases as someone else you should be in the clear. I think this age of copying use cases is now over and we're in a place where [AI] should be seen more as a platform for innovating and of course there are also obvious use cases that others also are doing and they should be utilized as well but when you have a new technology the sky is the limit in how you'd like to utilize it. [...] For instance with health care, you quickly come to the situation where, if you want to be in the very spearhead of new technology use, that stuff hasn't even been invented yet.
> - *Head of AI, Company D*

A fair point by the Head of AI of Company D notes that if one reads consultancy white papers and use cases and copies them, they are automatically trailing the industry. This is why this section is not meant to be read as a comprehensive listing of use cases that firms can pick from and then bolt on top of their own organizations. It is a way of classifying the rough directions and styles of AI use that have taken shape so far. The intent is not to be comprehensive, but rather to be descriptive and provide business leaders with a general idea of value production mechanisms of AI. Classifications rarely stand up to the test of time particularly well and often represent the way the classifier sees the world, rather than what the world actually is. This is not a major issue as long as it’s acknowledged and understood. Classifications can be immensely useful especially earlier in the lifecycle of a technology or a group of technologies though. They let us organize the world, in whichever arbitrary manner that may be, and help us understand the larger context of our actions or inactions.

In structure, this section differs somewhat from the previous sections in this chapter. As it discusses the main research question of the thesis, rather than the previous sections that discussed the subquestions, it builds its argument on top of the previous sections in this chapter. This means that the archetypes that are being showcased here are built upon quotes, concepts and discussions discussed throughout this chapter in sections 4.1., 4.2., 4.3. and

4.4., rather than just the quotes and concepts that are showcased here. The model used to depict the archetypes that cover the utilization models is the one built based on business model literature and introduced in chapter 2.9. It is explained in further detail in that chapter and thus won't be re-introduced here.

This section is a synthesis of all the interview data gathered for this thesis, and it should be read as one as well. The archetypes shown here were created by grouping informant comments that were coded as having relevant information in them in regard to the research subquestions and/or the main research question on the basis of the various dimensions of the composite model. Within these groups, further subgroups were created by arranging the comments around themes they contained. The themes were then classified under further headlines which eventually formed the utilization archetypes that are presented in chapter.

A classification system for the themes that not only saturated from the interviews when discussing the sentiments, business challenges, critical competences and business model implications of AI but also directly and explicitly with some informants was a three-pronged approach. AI utilizations were seen as roughly dividing into three separate streams of outcome: Cost-saving, consumer engagement and auxiliary benefits. This was curiously enough also an opinion that came up several times during the interview process in some variation from the informants. While all three utilization archetypes were not necessarily present at the same time in the comments by informants, the comments formed a whole which essentially covered all three and divided utilization styles among those very same lines.

4.5.1 Cost-Saving Archetype

A significant utilization style that formed on the basis of the interviews was one that focused on reducing some of the costs of the organization whether the origin of these costs was humans or otherwise. Here, the central value-delivery mechanism of the archetype revolves around freeing resources for other, more productive activities, whether speaking about money or human resources.

The best-case scenario right now seems to be freeing up the resources of the client. […] In addition to just a singular [AI] product that saves resources, the other side of things is making better products that produce added value to the end consumer. Contextuality enables us to offer offerings more correctly, raise adaptability and offer personalization much better than before.
- *Service Design Lead, Company A*

I guess usually the hope is that you get more efficiency, sales and probably better profitability […]. I'd like to think that it's also about investing into new things and building some proficiency internally but I'm not really sure how much it's that. Maybe some parties actually behave like that.
- *Director of Online Services Development, Company C*

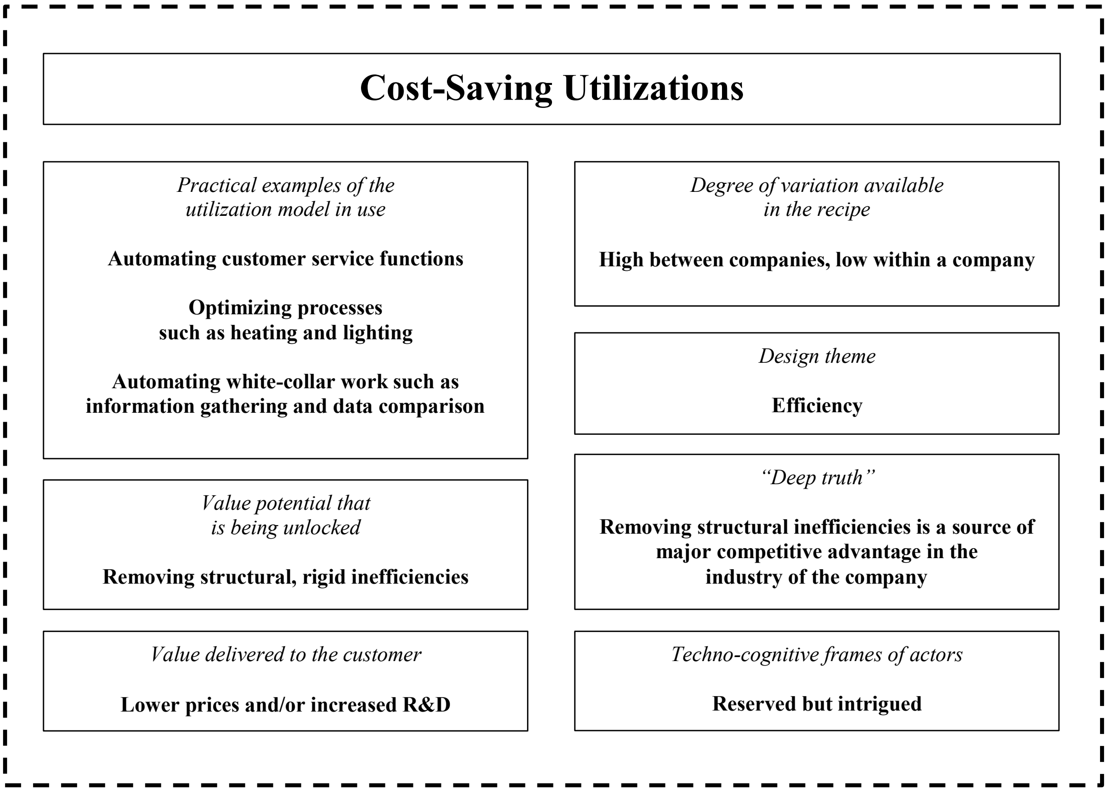

***Figure 6**: Cost-Saving Archetype*

Figure 6 illustrates the archetype of AI utilization that focuses on saving costs. Some of the practical examples of this archetype that came up during the interviews were utilizations such as automating customer service functions, optimizing processes with miniscule variations (but still enough so that rule-based systems would not be sufficient and humans too costly) such as heating and lighting and automating white-collar work that consisted of information retrieval, data comparison and other tasks that were thought to be squarely in the realm of human employees until a few years ago. As the theme of the archetype suggests, these actions all were directed towards controlling and reducing the costs of doing business. They were not investments in the core product or improvements of it (although that might be debatable in the case of automating certain human tasks) but merely made certain repetitive, predictable processes quicker or in some cases instantaneous. The unlocked value potential is simply the act of getting rid of rigid, structural inefficiencies that were so ingrained to the business or the industry that removing them was perhaps not even actively thought of. Optimizing server hall cooling to the point of real-time microadjustments is a great example: While cooling massive server halls was a business challenge, it was a business challenge where the optimization limit seemed to be achieved and additional marginal utility from investments was negligible. When it comes to this value being delivered to the customer things get less than straightforward. Here, the firm has the option to choose how they want to spend the capital that they have just saved by optimizing processes or raising the productivity of the workforce. This can of course be passed down as savings to the customers in the hopes of raising the demand for the product or it could be used for investments into R&D and other parts of the company or, finally, it could just be paid as dividends to the shareholders.

The degree to which this archetype can be varied naturally is different from company to company, although an individual company typically most likely has quite stable sources of inefficiencies and rigidities due to its business model and management system. From the four design themes specified in chapter 2.9., this archetype falls into the theme of "Efficiency" quite naturally. The deep truth recognized in this archetype is the idea that the competitive situation of the industry is such that any amount of shedding of inefficiencies or structural rigidities that the competitors are also suffering from (server hall cooling costs, the man hours needed to look up information in a management consultancy, for instance) translates into a competitive advantage of such size that it is in the interest of the company to do so. The techno-cognitive framing that actors exhibited in discussions that pertained to the cost-saving archetype seemed to be reserved but nonetheless genuinely intrigued. The amount of hype that was around the topic was recognized and taken into account but the cost reductions in the overall business seemed to serve as proof of the technology's potential.

4.5.2 Customer Engagement Archetype

The second archetype of utilizations recognized during the interview process was focused on driving customer engagement and improving the product itself. This may include improving the performance of the product, the perceived quality of the product, shortening the amount it takes to deliver the product, or even improving the marketing of the product so that the customer finds it more beneficial and closer to their interests. As was expected, this was an area with a large amount of diversity and goals within it but it still formed a clear, coherent group of utilizations with a unique philosophy.

> In a company of this size, they are related to the efficiency of processes, quality of them and, on the other hand, the customer experience and how that presents itself in the grocery store or online or in our logistics model. Things like getting products at the right time to some place, ensuring that they are fresh and minimizing waste, pricing etc. There are many things, depending on the case of course. The thing I try to also emphasize is the fact that there needs to be either a problem that the customer has or a problem that we have that we start solving. […] In essence [AI] brings better profitability for us, in two ways. Either it's cost savings or better margins in the processes.
> - *Head of Analytics and Customer Data, Company C*

Here, the informant mentions better margins in the process, the quality of processes and customer experience. Things such as the correct timeframe for delivering products, ensuring that they are fresh and other notions are mentioned as examples where AI can provide meaningful improvement in the consumer's life.

> For now, we have focused on working at the consumer level where are goal is to raise the level of service that the consumer receives, which in turn leads to the consumer preferring to do business with [Company C] and brings additionally business to us and that translates as additional profits. […] One simple area where we have gained actually very measurable business benefits is simply more accurate targeting of marketing to our customers. In practice, our [AI] model calculates constantly what kind of content we should show to the customer in email advertising and other marketing. Simply by being able to pick from all different offers that are ongoing at any given moment just the right one has garnered quite substantial results.
> - *Chief Data Analyst, Company C*

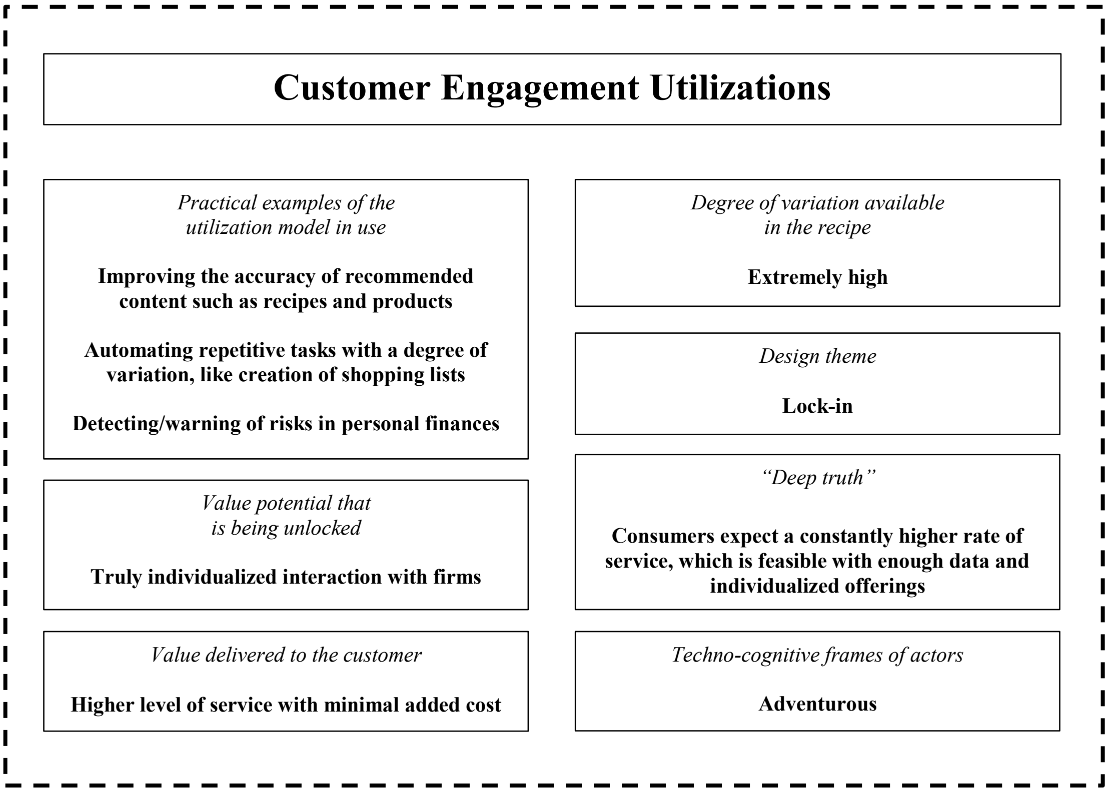

***Figure** 7: Customer Engagement Archetype*

Figure 7 examines in detail the Customer Engagement archetype of AI utilizations. The practical examples in the archetype are perhaps of dubious importance as they pertain so heavily to the individual focal company. Some of the more practical examples of this archetype related to more accurate and thus better targeting of recommendations to customers, automating tasks the customers needed to do to engage with the company (like building shopping lists for grocery shopping) and detecting and warning of hard-to-detect subtle risks in personal finances. They are utilizations which make the experience of engaging with the company easier, more pleasant or richer. The value potential follows along these lines, in that it shifts the concept of individualized service to the realm of reality, depending of course on the quality of data the company has managed to gather of its customers. For the customer, this means a higher potential level of service with minimal added costs. Minimal added costs are, naturally, a promise that is in the discretion of the company itself, whether it wants to move the R&D costs of AI systems to the consumer. The degree of variation available is deemed extremely high due to the creativity that this utilization archetype makes possible for the organization. The design theme for the archetype of customer engagement is quite clearly Lock-In. The idea of bettering the product and bringing richer, deeper individualized offering is to promote customer loyalty and frequency. This is something that was explicitly stated in numerous interviews. The utilizations in this archetype are built upon the assumption that the customer has a tougher time abandoning the company and its products if they are, simply, too good to not use, effectively locking in the customer. The deep truth exhibited by this archetype of utilization is that the demand for a higher level of service by consumers is theoretically endless, so that is a sustainable path to growth for the company as well, unlike cutting costs or prices which have a limit of 0 (theoretically). The actors who talked of utilizations in the Customer Engagement archetype seemed to be quite adventurous and open-minded in their efforts, with a tolerance for failure. They essentially saw AI efforts as an investment on par with other investments, in that they may fail and have no ROI whatsoever.

4.5.3 Auxiliary Benefits Archetype

The three quotes below take into account a third, less obvious utilization archetype: The auxiliary benefits of AI utilization. These are benefits that spring from AI utilization that are not directly associated necessarily with the core business of the company, the cost-profit function of the company or the core product of the company. They offer benefits that are created as a *side effect* of AI utilization. It should be noted that they are not necessarily benefits that are born accidentally or as a consequence of a happy coincidence. On the contrary, as noted in the quotes, they can be rather deliberate and well-understood.

> Some of it is efficiency and cost-saving, that's a major driver. Companies with public-facing content, like media houses, have an interest in driving retention. Like recommendation solutions are an obvious way of doing that. Then there's some more on the kind of marketing side… Even if the project doesn't have obvious monetary value in and of itself just the fact that "hey we're cool and we're doing it". I guess those are the biggest ones: driving cost-savings, driving engagement with the product and one is just purely marketing.
> - *Senior Data Scientist, Company B*

> Then we also have these entirely new services and intelligent services that strongly emphasize a new kind of customer benefit. This means personalization, recommendations, actively advising the customer and building mechanisms that can predict certain risks and prevent them as well, in all segments of our business. Lastly, in our internal development are completely new business models that are born from data and these new capabilities, so that we can also create new business from them. That means that if we invest into AI capabilities, why wouldn't we also license those same capabilities to somewhere outside of Finnish borders?
> - *Head of AI, Company D*

Here two informants note that there are different, separate benefits that may accrue from AI development which can be interesting enough as sources of value on their own. While the marketing value of AI projects is obviously subject to diminish as AI goes increasingly into the "boring" mainstream it is something that can be leveraged in the early stages of it. The same can be said about licensing new technology which obviously has a far stricter deadline on the value it provides in the form of patents and other intellectual property rights.

> On some level I'm just so simple that I think it's really either that you improve your profitability and efficiency or you grow and serve your customers better. Those should be pretty much it. Those are the drivers that should, for instance, raise your NPS. Or those are the things that raise your customer satisfaction and then improve your sales as well, and in that way grow your market share. I think that [AI] should always have link to those things. Note that I also count free media visibility as something that has a direct link to those. Eyeballs are not free. They also have value, sometimes [the utilizations] can be more like that as well. Like experiments, where Kauppalehti [A Finnish business daily] writes that hey check out this cool AI thing.
> - *Senior Business Designer, Company B*

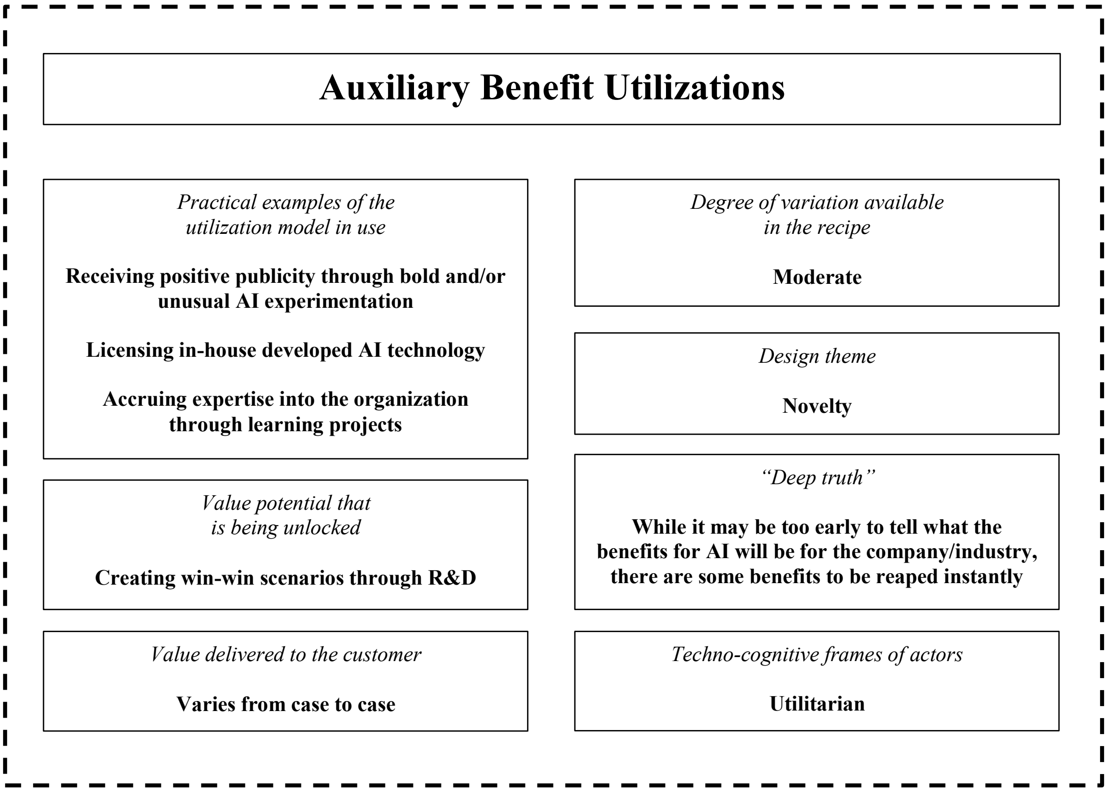

Figure 8: *Auxiliary Benefits Archetype*

Figure 8 examines the Auxiliary Benefits archetype in more detail. As one can imagine, the practical examples of this archetype in use are extremely varied as they do depend on the individual strategic needs and aims of the organization, however some throughlines could be seen in the interviews. A number of informants mentioned that engaging in AI projects was a fully viable strategy of garnering earned media in form of PR attention, especially when the said AI projects were interesting enough. Furthermore, certain informants noted that while nothing may come out of an AI project at this stage of the technology's maturity, they are useful for organizational learning in regard to the technology and their value may realize much later when it is absolutely critical that AI can be integrated swiftly and effectively into the core business of the organization. Lastly, the idea of developing AI technology and licensing it was floated as well. Most AI frameworks as of writing the thesis are open source technologies such as TensorFlow and Torch and, according to the data scientists interviewed, they seem to be widely used in commercial projects as well. However, this does not mean that even as of writing this larger technology companies don't have their own proprietary systems as well, working with tandem with open source tools. In fact, these seems highly likely. Licensing these systems may indeed be a viable form of revenue for companies. The value potential unlocked here is rather clear and unceremonious: unlocking win-win outcomes from R&D projects, in essence hoping that they deliver auxiliary benefits on top of their primary benefits. The customer value of the utilizations in this archetype varies heavily from case to case. In some cases, there simply is none. It is debatable, for instance, that what is the value of a better image of a firm for the customer. They may feel that the company they are interacting with is more prestigious and gain certain value from that but that is obviously extremely subjective. While the cases are quite varied, the variation in their outcomes is quite moderate. They boil down to PR benefits, learning benefits and financial benefits. The overarching Design Theme here is Novelty, the idea that there is an inherent value in newness that will translate into value for the focal company. When it comes to a deep truth, there is not anything overly salient that stands out, except perhaps the investment strategy in regard to AI which this archetype implies. The strategy is a conservative one but at the same time seeks to reap rewards without being too difficult to execute within the company politically speaking. The techno-cognitive frames of actors seemed to be quite utilitarian in regard to the Auxiliary Benefits archetype, where they understood the relative immaturity but also the pressure of boarding the boat on AI before it was too late.

5 Discussion

In this chapter, the findings of the study will be discussed and a dialogue with the extant literature will be formed in order to attempt to understand the results in light of an academic-managerial perspective.

The purpose of the study was to understand the value creation mechanisms and styles of AI utilization by understanding and researching what kind of archetypical utilization models for AI had been created so far. In order to understand the key concepts and critical factors in value creation and new technology exploitation in business, appropriate academic literature was studied extensively. The literature review that was created from the basis of this can be read in chapter 2. At the end of chapter 2, in section 2.9., a composite model was formed based on the literature that was reviewed in order to provide a framework for discussing the utilization archetypes in and providing them with business dimension to address.
In chapter 3, a set of questions was formed for the informants to answer to that were also based on the literature reviewed in chapter 2. The findings of these interviews were discussed in chapter 4. Based on the interview data as a whole, three archetypes of AI utilization were formed in section 4.5. These archetypes used the entirety of the interview data as their source material to categorize AI utilization by businesses into three separate, well-defined yet highly individual categories. They focus on practical value creation aspects and business model implications of utilizing AI, which is appropriate as the source material also focused deliberately on the business aspects of AI use.

5.1 What kind of business challenges do AI utilizations address?

Three central groups of business challenges were identified that AI utilizations so far had focused on addressing, according to the interview informants: *Reducing manual labor, getting rid of human bias and solving problems that were previously unfeasible to solve*.

While not entirely unpredictable, it was intriguing to see that the business challenges the informants expressed AI to be most useful for and addressing so far were quite unique in their nature and leveraged the unique capabilities of AI technologies well, rather than being too general in their nature. The first one of these business challenges came as no surprise for anyone who has followed any of the discourses on AI that were detailed in chapter 2.3. Reducing manual labor and gaining cost advantages through automation has been the dominant narrative of AI for most of recent years. The idea of AI as a harbinger of unemployment through automation should be familiar to anyone who has followed any news on AI technologies and their progress. While it may seem overblown and unlikely, it is not without a certain amount of truth. Automating certainly rose prominently as a topic of interest during the interview process, and perhaps naturally so given the capabilities of the technology itself: If and when we are talking about a technology that is based on analysing large swathes of data and then applying that data to new situations that may often fold in real time, this in essence means automating sequences of action that have taken place before in some variation or another. Furthermore, the idea of cutting costs is certainly a popular application of a novel technology which has not yet reached the heights of its maturity. Abernathy & Utterback's (1978) notion of novel technologies' performance criteria being vague and poorly understood seems to hold true, as saving costs is a performance criteria that certainly derives from a time before AI innovations and qualifies essentially as a business heuristic: If a technology is capable of cutting costs, it is accepted as adequate. Innovations using new technology typically are initially developed to fight against the rising input costs of the business (Utterback, 1974) and such is the situation in here as well. Many informants stressed that the automatization that AI brings to table is capable of automating repetitive labor tasks that still are often done by, in many cases, highly trained skilled professionals. These are tasks like information retrieval, document comparison and producing reports. As more and more businesses rely on these types of tasks when moving higher on the value chain, the cost of their inputs rises significantly due to the education level required for many of these tasks. In this sense Utterback's (1974) theory, despite its age, holds up remarkably well, although it might be argued that automating repetitive labor is not simply a cost-cutting measure but more akin to a shift in the overall cost structure of the company, moving higher skilled employees to tasks that utilize their skill levels more sufficiently. This is certainly possible, but also in the end up to the companies themselves to decide.

The second business challenge that was addressed was the problem of human bias in business. Human bias is a useful tool when used purposefully and in a deliberate manner to solve highly complex issues that require contextual, abstract problem-solving but it can erode an organization's capabilities as well. Applicants get rejected due to foreign-sounding names, new business ideas are shunned because of their unorthodox thinking and investments get made and not made because of gut feeling. Understandably removing human bias is a major area of interest for companies that are willing to admit it. Danneels' (2002) idea of second-order competences, competences that are required to understand, incorporate and exploit new technology in familiar business settings seems to be in accordance with the challenge of relegating power to AI systems in situations where human bias would have previously influenced the decision making. This sounds relatively straightforward on paper but in fact it is far from it. If data-driven, AI-powered decision-making is to be truly incorporated into a firm, it either needs to make a human or a team of humans conform to the recommendation of the "machine" or needs to remove the humans from the decision-making process altogether. Neither of these options seem likely, and at this stage of the technology, advisable, yet the scenario nevertheless offers food for thought.

Lastly, the business challenge of solving problems that were previously unfeasible to solve was discussed widely by the informants. While this business challenge shares a strong kinship to automating repetitive tasks, it is more fundamental in its nature. The crux of the matter being that certain business challenges are taken as so given that they have, in fact, formed the actual framework that the entire business is built upon. They are so rigid that questioning them would be the same as questioning the entire business model or even the industry. Unfeasibility is the key operating word in this category, as they are things that often would be prohibitively expensive to develop and operate while they would be optimal to have from a strictly business point of view. A classic case might be a truly 24/7 customer service which would be capable of handling any customer service request at any time of the day. Certainly, these services do exist, but they are few and far between. Other examples might include personal finance stress tests and risk analysis for banks, which again is certainly happening, but it is not happening at an optimal level, which in this case would be continuously.

Understanding and applying AI technology in relation to these structural rigidities or previously unfeasible technical problems comes down to what Orlikowski & Gash (1994) referred to as technological framing. What is the role of the new technology in the organization? Some actors, in accordance to the theory of technological framing, will understand the technology as an opportunity to question truths that have stood unquestioned in the industry and the company. This enables the firm to tackle and find previously unfeasible problems.

5.2 What are the critical competences required for successful AI utilization projects?

A strikingly uniform set of answers from the informants produced the two critical competences that were required for AI projects to succeed: *Business expertise and cross-disciplinary collaboration.*

Business expertise may seem like a somewhat redundant result. Surely all the companies interviewed for the thesis were *businesses* which means that they should have *business expertise* embedded deep within them. Well, yes and no. While business expertise is certainly an area of expertise that is not as clear-cut in terms of resources and demand and supply as things like programming, data science, graphic design or sales, it is a surprisingly critical part of businesses and business units that are tasked with exploiting new technology to its fullest potential while still being in line with the company's overall strategy and vision. The informants expressed again and again, in perhaps what was the most unanimous single opinion of the entire data set, that business expertise was absolutely critical for AI projects to succeed. The oft-mentioned business expertise was tasked with bringing two distinct but interlinked deliverables to the table: Recognizing the problem that was worth solving (using AI) and formulating the exact way that the solution would deliver value both to the company and the customer of the company. This is extremely understandable because as stated in numerous times in chapter 4 and elsewhere in this thesis, AI is a "blank" technology, meaning that it does not do anything by itself. It needs to be adopted and integrated into the actual revenue-generating business of the company and it needs to be integrated in a way where the value outcomes are fairly explicitly understood by both the company and the customer of the company. In this way, it demands a certain expertise and knowledge from the company which does not have much to do with the actual technology in question but rather business effects of that technology, promoting the hiring of people under a diverse set of titles such as Business Designer, Development Manager, Business Developer and so on. This challenge of integrating and developing business models around new technological concepts is quite well understood and documented by scholars. Cohen and Levinthal (1990) spoke of absorptive capacity of the company, the capacity to understand and exploit technological inventions. This is essentially exactly what the informants talked about when they issued calls for “business expertise”. In addition, Chesbrough and Rosenbloom (2002) also have noted that the value in technology is latent until it is accessed through a business model. Again, same concept, slightly different wording. It seems that both scholars and the informants agree that it is imperative that people who have a background in understanding business and strategy are in a key role in building high-performance products and services that exploit new technology.

Another, closely linked finding in regard to critical competences in AI projects was the need for cross-disciplinary collaboration in AI projects. Here, the informants referred to some failed AI projects that had gained publicity and noted that they were typically not technical failures but design failures, failures that could have been averted with more non-technical thinking. The informants noted the need for cross-disciplinary collaboration that stemmed from the very fact that AI was so neutral and blank as a technology. In order to fully leverage it, domain expertise was needed. However, this domain expertise would need to be preferably combined with a certain, bigger than zero level of technical proficiency as well. This notion is not contrary to what Leonard-Barton (1992) posited about the core rigidities and core capabilities of the organization, and the fact that the core capabilities may sometimes inhibit innovations as they lay the baseline for what counts as an innovation in the first place. It does, however, emphasize the role of core capabilities in the innovation process. Similarly, Clark (1985) introduced the idea of design hierarchies and seemed to be quite critical of them. Design hierarchies have a time and a place too, it seems. The value of a design hierarchy is its ability to anchor the innovation to the core business of the company and while sometimes this may be inhibitive for innovation, it may also be absolutely crucial.

5.3 What are the business model implications of AI projects?

Business model implications, meaning the novel business models that may be created by the proliferation of AI projects, were also identified from the interviews with informants. These were *AI as a “booster”* and *humanity as a competitive asset.*

Multiple informants noted the use of AI as a booster technology, essentially using AI to “supercharge” the organizations core functions to a degree that they might affect the core business model itself. In some sense this shares traits to what was discussed in chapter 4.2.3., solving problems that were unfeasible to solve before. This is a fair comparison. When talking about unfeasible problems, one could of course categorize “exponential growth every fiscal year" as an unfeasible business problem that should be solved by the use of technology. That is, however, too general for our purposes in this thesis. The idea of acting as a booster is simply bringing something to a scale that was previously thought of as unattainable. In effect this means, for instance, personalization and targeting on a scale that was previously thought of as impossible, having such accurate data and understanding of every customer of a certain grocery store, for instance, that the selection could be tailored extremely specifically. This is similar to Henderson and Clark's (1990) idea of changes in the product architecture, meaning that the essential product stays more or less the same (a grocery store still seeks to buy inventory at the lowest price possible and then sell it at the highest price possible) but the product has reconfigured its own internal architecture to deliver higher value (the grocery store stocks *exactly* what its regular customers want without ever even asking them). The business model evolution comes from the fact that, theoretically speaking, this is a level of service that is quite easy to replicate by the competitors of this grocery store and thus selection no longer provides the competitive edge it used to provide for the entire previous lifespan of the industry and that edge will need to be found elsewhere.

Humanity can also shape into a unique competitive asset and a source of differentiation. This interesting and slightly dystopic (or utopic, depending on who you ask) idea was floated by a few informants who noted that if AI systems proliferate to such a degree that receiving customer service from a human being becomes rare, humanity itself can form into a new selling point for certain companies. The simplest and most probably the most realistic example of this might be that of customer service. If customer service faces a wave of automatization in form of chatbots and possibly other types of AI systems, the availability of human contact in customer service will reduce dramatically. Assuming now that the demand for human contact stays at a stable level (and this certainly is a big if. Perhaps yearning for human contact in customer service will be a thing of the past and customer service will simply transform to mean automated customer service systems at some point), the scarcity of human contact has just gone up. Now, the question is: what is the premium that is placed upon interacting with humans? Will some people be willing to pay that premium? Is it enough to provide a company with a competitive edge? These are questions that markets are able to answer quite accurately but we will unfortunately have to wait for an answer. It is prudent to note that this may have quite significant business model implications for companies who now operate in the upper segments of their markets or wish to move strategically into more premium segments. A luxury hotel derives much of its luxuriousness from the fact that there are numerous humans around who provide the guest with human care, meaning care that understands contextual nuances. This form of luxury may soon be seen in other industries as well. The idea of providing customers something that they value is in the heart of business model literature. Demil and Lecocq (2010), for instance, stress the fundamental importance of articulating different areas of a firm's activity so that they produce a proposition of value to the customers. As such, the business model of any business is not to do business or sell the products or services they sell currently but to provide value to their customers, meaning that in the future one way of doing so may be simply by offering more human-centered services as opposed to automated ones. A connection can also be drawn to the idea of the "deep truth" as introduced by Teece (2010). Perhaps the deep truth of AI is that a number of services derive a significant portion of their value from the human element within them and removing this human element drives down the perceived value a great deal, which in turn can be exploited for business gains elsewhere.

5.4 What are the archetypes of AI utilization?

Three principal archetypes of AI utilization were formulated on the basis of the subquestions discussed earlier and the entire interview data. These archetypes hold within them a large range of AI utilizations and their value capturing strategies. They are *the cost-saving archetype, the customer engagement archetype* and *the auxiliary benefits archetype*. These archetypes are discussed in detail in chapter 4.5. and modelled there using the framework that was developed in chapter 2.9.

The cost-saving archetype (figure 6, section 4.5.1 of chapter 4) is quite straightforward in its utilization model: it is an archetype that aims for maximizing the cost-saving effects of the AI and thus it mostly focuses efforts on the optimization of the cost-driving operations of the organization. This is understandable, logical and seems to be in line with the trajectories of some of the other new technological paradigms from history. One of the more straightforward ways of improving the bottom line of a business is to cut costs, so it is understandable that many new technologies do get "relegated" to this role when they are first making their way into an organization (Utterback, 1974). This is also naturally an easy sell internally, politically-speaking: cost-cutting is perceived as a neutral way of improving the business and has typically no major shifts in power balance associated with it, which is not the case when making product quality investments or larger strategic choices about the roadmap of the company. However, ne should not be cynical of this archetype and its existence. Cost-saving is a more complex and strategic matter than it may seem at first glance.

Efficiency in resources and achieving a higher degree of profitability were mentioned several times by the informants throughout the interviews. However, virtually none of the informants at any given time felt that driving higher and higher efficiency would be the sole goal of any organization or technology. This is not surprising for at least a couple of reasons. Efficiency and cost-saving are in fact *not* the goals of any organization, save for some highly specialized government institutions. Cost-saving is a means to an end, which is greater profitability and higher returns for the shareholders of the company. On the other hand, there is a certain stigma about focusing on cost-saving and reducing inefficiencies, especially when it comes to AI. As AI systems are capable of performing quite complex and vague tasks with multi-faceted rulesets, developing them as tools for saving costs often means retraining or laying off employees. This is certainly the central tension of AI progress in the public discourse, which may contribute to the willingness of the informants to discuss cost-saving schemes in greater detail.

The actual measures themselves happen through finding certain structural rigidities in the cost structure of the business and eliminating them by using new technology that was previously not available (AI, in this case) and historical data, provided that it exists and is of high enough definition to achieve this. The idea of using AI as a cost-saving tool also seems to be in line with Danneels' (2004) notion of disruptivity being in the eye of the beholder. AI can be a very disruptive technology for some companies and industries but for some it is a sustaining technology that helps to drive down costs, and perhaps not much else.

Customer engagement archetype (figure 7, section 4.5.2 of chapter 4) attempts to create and capture value using a different mechanism, one where the company invests into the core product using novel business technology (in this case AI) with the goal of bettering the product to such a degree that it attracts either new customers in a volume that offsets the amount of investment or drives up frequency and/or loyalty of current customers in a sufficient manner to justify the investment.

The source of value to the firm is markedly different than in the first archetype. The utilization style that is described here is not about efficiency or saving money, it is about investing money. The investment strategy here, so to speak, is about driving customer engagement and raising either the loyalty of the customer or the volume of business through that. Like all investments, it carries a risk of not realizing: It is a bet made about the product that the product will improve with the use of AI. As a strategy of technology utilization, it is naturally somewhat riskier than cost-saving because of the bet-like nature of it.

The practical utilizations themselves typically affect the accuracy of the service in relation to the individual customer and their needs, as this is something that this set of technologies happens to do particularly well, although the archetype is not limited to only this. Essentially any forward-facing investment that aims at increased revenue (as opposed to decreased costs) would be filed under the archetype. Here, the value is transmitted squarely to the customer as the company is so dependent on the customer to make the investment worthwhile. As already alluded to before, while this is the archetype that is perhaps most visible and the flashiest it may not yield sustained competitive advantage at a rate that would be comparable to the other archetypes. This is simply due to the dynamics of competition: If a new, higher AI-powered service becomes the de facto standard in an industry, it is no longer a competitive advantage but a requirement. This approach to value creation is certainly closer to what Chesbrough (2010) had in his mind when he talked of companies commercializing technologies. In the context of this thesis it’s important to note that this archetype, however popular or appealing, is in the end equal to the two others and just a different philosophy of approaching a new, relatively immature technology.

The final archetype of utilization that was discovered from the interview data was the archetype of auxiliary benefits (figure 8, section 4.5.3 of chapter 4). This is an archetype that differs significantly from the two others, as it derives its values from what are essentially side-effects of AI projects and not the actual technological outcome that is being developed. It is crucial to note that the utilizations in this archetype are done *deliberately*, as accidental side-benefits can happen with any project and are typically not seen as the main source of value.

Examples include marketing and PR benefits that come from the relative novelty and exoticism of AI, new and unseen business models and business cases, licensing AI technology and methodology and organizational learning. The point of exhibiting this as its own utilization category is to point out the fact that in some cases it may make strategic sense to engage in new technology projects for reasons other than direct benefit to the bottom line or direct benefit to the customer. It might be suitable to note that some of these situations are fairly specific and most likely probably not recommended for organizations who don't have very experienced and well-managed R&D teams. This archetype of AI utilizations is not either (necessarily, at least) a product of cynicism or overt caution in regard to the technology itself. This is a perfectly viable archetype of utilization if it's not entirely clear what the benefits of a technology might be for the company but it is clear that the technology holds so much potential that the opportunity costs would simply be too high to invest in something else. As said before, this archetype requires perhaps what is the greatest strategic and predictive abilities from an organization as it is the most future-oriented as well.

While not cynical, the utilizations in the archetype are typically quite realist about the benefits that AI will bring to the organization and have an optimistic outlook on the side benefits. This is an archetype that is probably more typical in the early stages of technology maturity as the benefits of a technology are much more known and better understood the later we are in its lifecycle. The sources of auxiliary benefit are quite varied, as one can imagine, as the amount and type of auxiliary benefit also changes from organization to organization. For some, it may be about learning the technical aspects of AI development so that they raise their readiness for when the technology matures more and becomes perhaps business-critical. Kaplan and Tripsas' (2008) concept of technological framing affecting the very trajectory of the technology itself creates an interesting interplay with the third archetype. If the technological frame of the actors is that of realist, almost pessimist utilitarianism, then the trajectory of the technology also might morph into something rather underwhelming, never graduating from a position of bringer of auxiliary benefits to something more valuable.

6 Conclusions

6.1 Research summary

The purpose of this research was to understand the practical aspects of AI use in business, the value creation methods of AI and to build a robust yet flexible way of categorizing AI use into principal archetypes that serve as a tool for further discussions on the topic, both academically and managerially.

This was achieved by combining concepts and methods from scholarly literature pertaining to the diffusion and exploitation of technology and from literature on value creation and business models. Based on this literature, a model of an archetype of utilization was built, which was used to describe different utilization styles of AI and their mechanisms of value creation.

The empirical data for the study was acquired by interviewing employees who worked on AI projects in four different companies – two companies that were identified as AI vendors and two companies that were recognized as end users of AI technology. 12 people in total were interviewed from the companies in semi-structured interviews with questions that were based on the literature review of the study.

On the basis of the interview data that was gathered and analyzed, three subquestions of the study and the main research question were answered. The subquestions unearthed the main business challenges addressed by AI utilizations, the critical competences required to develop successful AI utilizations and the business model implications of AI as a technology. The main research question produced three distinct yet interconnected archetypes of AI utilization: The cost-saving archetype, the customer engagement archetype and the auxiliary benefits archetype.

This study has contributed to the academic research stream of technology strategy research and that of business model research. It aimed and accomplished to model a novel, emerging technology and its business use cases by creating a typology through which it could be analyzed and understood from the perspective of practical value creation.

6.2 Limitations of the study

As any master's thesis, the study has several limitations. Because AI is still a relatively young technology as far as business feasibility goes, there is regrettably little business research that has been published in high-quality peer-reviewed journals that discusses the effects of AI on business. In practice, this means that for the study other past business technologies had to perform a stand-in role for AI when it came to the literature review. Fortunately, this is fairly commonplace in business research where new technologies pop up regularly and some analogies have to be drawn in order to be able to speak about them and anchor them into a historical continuum.

The methodology of the study essentially means that the researcher has a somewhat active role in directing and influencing the informants during the interview discussions. This, of course, is a central feature and flaw of a semi-structured interview. It enables a more natural and fruitful interview setting that may lead into more candid, informal discussions but it also strips the interviews of complete neutrality per se. It is certainly debatable whether a structured interview would be neutral either since the setting itself is unnatural to begin with.

While the sampling of the informants was not small by any means, the results of the study should not be treated as generalizable facts because those they certainly are not. This is not a quantitative study or a survey about AI use: It is an attempt to formulate a system for categorizing utilization archetypes. Finally, it goes without saying that this is a master's thesis and not a peer-reviewed journal paper. The author is not a professional researcher and as such the work itself should not be compared to work of professionals as it lacks the nuance that experience always brings to the table.

6.3 Suggestions for further research

A natural avenue for continued research on business use of AI would be to conduct a quantitative study, in Finland or otherwise, to attempt to see whether the categorization scheme created and presented in this study reflects the statistical reality of AI utilization. As noted several times, we are dealing with a fairly novel technology. This is why the topic is especially suited for further research and in fact dependent on it. It would be extremely interesting to see how the field of AI utilization in business has developed in 5 years or 10 years or even further.

Originally, this study also intended to incorporate public sector AI use. It was dropped because the complexity of the subject and its incompatible nature with private sector comparisons. However, the public sector has been extraordinarily active in its embracing of AI technology in Finland and that would be an interesting topic for another thesis or perhaps even a research paper. The public sector needs to comply with a very different set of privacy rules as well, so it might be interesting to examine whether that has any effect on utilization styles and value creation in AI utilizations of the public sector.

6.4 Theoretical contributions

This thesis has taken part in the scholarly conversation about innovation management, technology strategy and business model research. As already discussed at length in chapter 5, it seems that most of the theory that was reviewed and studied for this study still holds water. Especially the notion that was already presented as early as by Utterback (1974) that novel technologies are often initially relegated to the task of cost-saving where they need to prove themselves seems to be true still more than 40 years later. This is a fascinating intersection of new and old and shows that longevity of results in business research is perhaps not as rare as it seems at the first glance. However, it is important to note that the novel technology examined in this case, AI, was not solely relegated to the role of a cost-saver either. Rather, it had a multitude of other roles as well despite its novelty. In this sense, Utterback's (1974) argument was still found to be correct but with some additional caveats. In addition, some replication could also be found in the domain of business model research from the more recent years. Several scholars (Chesbrough, 2010; Demil and Lecoq, 2010; Teece, 2010; Zott, Amit and Massa, 2011; Fichman, 1992) have noted the importance of business models and business acumen in the role of commercializing new technologies and/or products. This was also confirmed by the study as the informants stressed the importance of business expertise in commercializing the technology and understanding what was the problem that was worth solving.

6.5 Managerial implications

The managerial implications of this thesis are diverse and deep. They offer in quite clear and concise terms the main business challenges that AI utilizations have addressed so far. The style of the thesis has been very practical in the sense that by now, a fair amount of managerial implications have already presented themselves to the reader. This section will present a compiled version of them. Reducing manual labor, getting rid of human bias and solving problems that were previously unfeasible to solve are areas of business challenges that any manager can find connecting points to their own organization. The key business challenges that have been addressed by AI utilizations so far were detailed in chapter 4.2 and hopefully they serve as a source of inspiration and food for thought for managers who are looking to leverage AI technology in their organization but are unsure of where to start from.

Managers seeking to build successful teams that exploit new technology to its fullest value-creation potential should pay special attention to chapter 4.3. In this chapter, two aspects were raised above others in terms of competences required for successful AI projects: Business expertise and cross-disciplinary collaboration in the organization. These competences certainly do arrive with the caveat that there needs to be enough technical competence and data resources in the organization as well.

Chapter 4.4 discusses some of the business model implications that managers should be aware of that may rise from the continued proliferation of AI technologies and AI projects. The idea of AI as a booster technology for any sufficiently formal activity of an organization and the notion that humanity may soon become a premium commodity that holds differentiating power are both future-oriented thoughts that hold relevancy in almost any industry. The key managerial question remains: How much?

Finally, chapter 4.5 presents the main outcome of the study, the three archetypes of AI utilization and their individual traits. Cost-saving, customer engagement and auxiliary benefit archetypes are general enough to be useful and flexible archetypes for any type of organization, but they contain enough detailed information to give clear directions and restrictions for their potential users. They represent the materialized form of the approximately 13 hours of recorded discussions that were conducted with industry experts for this thesis. I sincerely hope that the reader of the study will find them inspiring, engaging, thought-provoking and even useful.

As everything in life, the archetypes presented in here will age and become obsolete one day in the future. This is an inevitable part of any work that examines the world and its phenomena as they unfold. What will hopefully live on are the depictions of the actions of different actors that have been represented here, their thinking and their strategic reasoning as a sufficiently accurate snapshot of the world in the early days of AI utilization in business.

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